Stock Returns Predictability and the Adaptive Market Hypothesis: Evidence from India

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Abstract The present paper evaluates whether the adaptive market hypothesis provides a better description of the behavior of Indian stock market using daily values of Sensex and Nifty, the two major indices of India from January 1991 to April 2013. We employed linear and nonlinear methods to evaluate the hypothesis empirically. The linear tests show a cyclical pattern in linear dependence suggesting that the Indian stock market switched between periods of efficiency and inefficiency. However, the results from nonlinear tests reveal a strong evidence of nonlinearity in returns throughout the sample period with a sign of the taping magnitude of nonlinear dependence in the recent period. The findings suggest that Indian stock market is still in the first stage of AMH and hence calls for an active portfolio management for excess returns.

Keywords: Adaptive market hypothesis, Market efficiency, Random walk, Autocorrelation, Nonlinearity, Predictability, behavioral finance.

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There is no theory, which has attracted volumes of research like efficient market hypothesis (EMH) over four decades. It is the well-known, yet highly controversial theory of Neoclassical School of Finance which has influenced modern finance in both theory and practice. Fama (1970), who explicitly formalized EMH states, "A market in which, prices always 'fully reflect', available information is called 'efficient'[1]. In such a market, when new information (news) arrives, security prices quickly respond and incorporate all information at any point of time, and reach a new equilibrium. Moreover, in such efficient markets, collection of information is costly and there will be no returns on such actions. Hence, it would not be possible to earn excess returns in an informationally efficient market. Under such conditions, fundamental or technical analysis cannot outperform a simple strategy of buying and holding diversified securities. In other words, the EMH rules out any active portfolio management[2].

Despite a large body of research on EMH both from developed and developing markets, the consensus on this issue that whether markets are efficient or not, thus continues to be elusive. In recent years, although there is striking evidence that stock returns do not follow random walk and possess some component of predictability, there is a lack of strong alternative theoretical explanations to EMH. Nevertheless, recently Lo (2004) has proposed an adaptive market hypothesis (AMH) based on an evolutionary approach to economic interaction, which can coexist with EMH in an intellectually consistent manner. It is stated that the emerging and developing markets have more tendency to reject EMH because of several market frictions. Unlike EMH which assumes a frictionless market, AMH accommodates market frictions and

[1] The seminal work of Bachelier (1900) laid theoretical foundation for the theory of efficient market. The pioneering work of Samuelson (1965) added rigour to the theory of stock market efficiency.
[2] Malkiel (1973) writes to the extent that 'a blindfolded chimpanzee throwing darts at the Wall Street could select a portfolio that would do as well as the experts'.

asserts that market evolve over a period of time. In light of this, the present article aims to determine whether AMH provides a better description of the Indian stock market, one of the emerging markets. To the best of our knowledge, there are no studies of this kind in India.

The remainder of the article is structured as follows. Section 2 provides a brief overview of adaptive market hypothesis and previous work. Section 3 describes data and econometric methods implemented for estimations. Section 4 discusses the main results and evaluates the relevance of adaptive market hypothesis for India. Section 5 concludes.

2. Adaptive Market Hypothesis

Lo (2004) offers an alternative market theory to EMH from a behavioral perspective, according to which, markets are adaptable and the markets switch between efficiency and inefficiency at different points of time. Lo (2004) applies the evolutionary approach of biology to economic interaction and explains the adaptive nature of the agents and consequently how market becomes adaptive. According to Lo (2005), "degree of market efficiency is related to environmental factors characterizing market ecology such as the number of competitors, the magnitude of profit opportunities available, and the adaptability of the market participants. In contrast to EMH, which assumes a frictionless market, AMH asserts that the laws of natural selection or "survival of the richest" determines the evolution of markets and institutions in real world markets which have frictions.

Unlike investors in efficient markets, investors do make mistakes and then they learn and adapt their behavior accordingly in the framework of AMH. The AMH has a number of practical implications. First, the risk-reward relationship changes over time because of the preferences of the populations in the market. Second, the movement of past prices influences the current preferences because of the forces of natural selection. This contrasts the weak form of efficiency where history of prices are of no use. Third, in adaptive market, arbitrage opportunities do exist from time to time. From an evolutionary perspective, the profit opportunities are being constantly created and disappear. This calls for investment strategies according to the market environment. In other words, AMH implies "complex market dynamics" which necessitates the active portfolio management. Fourth, innovation is a key to survival and AMH suggest that adapting to changing market conditions ensures a consistent level of expected returns. Finally, market efficiency is not an all or none condition but a characteristic that varies continuously over time and across markets[3]. Hence, a financial market may witness the periods of efficiency and inefficiency.

The AMH though still in its infancy, is attracting attention from researchers. Ito and Sugiyama (2009) find time varying market inefficiency in the US. Charles *et al*. (2010) holds AMH true in case foreign exchange rates of developing countries where they find episodes of return predictability depending on market conditions. Kim *et al*. (2011) tests whether the US stock market evolves over time in the US. They find market conditions as the driving factors of predictability and market is more efficient after 1980s than the previous periods. Exploring the relative efficiency, Noda (2012) concludes that TOPIX support AMH while TSE2 does not in Japan. Alvarez-Ramirez *et al* (2012) provides evidence in favor of AMH and note that the US market was more efficient during 1973 to 2003. Urquhart and Hudson (2013) document mixed results for the US, the UK and Japan markets and conclude that the AMH provides a convincing description of these markets.

[3] Campbell *et al* (1997) note that testing of market efficiency as a condition of all or nothing is not useful and such an efficient market is the economically unrealizable ideal market. They suggest relative efficiency because measuring efficiency provides more insights than testing it

Given the importance of AMH, the objective of this paper is to examine whether the Indian stock market evolved over a period of time and does AMH provides convincing explanations for such an evolution. This assumes importance in the backdrop of the financial sector reforms in India which were introduced in early 1990s to infuse energy and vibrancy to the process of economic growth. In addition, the drastic changes in the market microstructure and trading practices from 1994 onwards sought a transparent, fair and efficient market. As a result, India's financial system grew by leaps and bounds. As per the S & P Fact book (2012), Indian stock market now has the largest number of listed companies on its exchanges. The growing percentage of market capitalization to the GDP and the increasing integration of the Indian market with the global economy indicate the phenomenal growth of the Indian equity market and its growing importance in the economy. The capital market of India emerged as one of the important destinations for investment. The foreign institutional investors (FIIs) in particular are highly interested in Indian stock market for portfolio diversification and higher expected returns. Hence, the Indian stock market has received ample attention from the international media and academia. Notwithstanding the recent notable growth, investors, traders and policy-makers have their own misgivings regarding the efficiency of the Indian stock market.

There are studies which have empirically tested EMH in context of India but the findings are mixed (E.g. Rao and Mukherjee 1971; Sharma and Kennedy 1977; Barua 1981; Amanulla and Kamaiah 1998; Poshakwale 2002 among others). Departing from the previous studies on efficiency of Indian stock market, the present study has made the following improvements. To the best of our knowledge, this is the first comprehensive work on Indian stock market, which examines the AMH. Thus, the present article complements literature on AMH and extends existing work that that has examined efficiency of Indian stock market. Besides, the available studies refer to the 1980s and early 1990s and hence could not capture the changes in the nature of stock market efficiency in the post-financial sector reform and drastic transformation in market microstructure of the Indian stock market. The present study covers the period (1991 to 2013) of such changes is in order. Further, the majority of the studies in India used conventional tests to examine the issue of market efficiency. The present study has employed certain state-of-the-art methods and techniques, which are first of their kind in the Indian context. Finally, the issue of nonlinearity in stock returns is addressed in this paper has not received due attention in India.

2. Methodology

For empirical testing, this study uses daily values of Sensex and Nifty, the major indices traded in India and together constitute 99 percent of total market capitalization. The Sensex data is from January 1991 to March 2013 while Nifty data spans from January 1994 and March 2013. To capture changing efficiency or evolving nature of the market, the whole sample is divided into two yearly subsamples. Urquhart and Hudson (2013) has proposed a five-type classification of behavior of stock market returns over time depending on dependence and independence of returns: efficient, moving towards efficiency, switching to efficiency / inefficiency, adaptive or inefficient. We use this classification to evaluate the relevance of AMH in explaining stock returns in India. The present study implements both linear and nonlinear tests for empirical testing of AMH. The following subsections offers a brief description of these tests.

2.1 Linear Tests

2.1.1 Autocorrelation Test

Autocorrelation estimates may be used to test the hypothesis that the process generating the observed return is a series of independent and identical distribution (*iid*) of random variables. It helps to evaluate whether successive values of serial correlation are significantly different from zero. To test the joint hypothesis that all autocorrelation coefficients ρ_k are simultaneously equal to zero, Ljung and Box's (1978) portmanteau Q-statistic is used in the study. The test statistic is defined as

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \qquad \text{. . . (1)}$$

where *n* is the number of observations, *m* lag length.The test follows a chi-square (χ^2) distribution.

2.1.2 Runs Test

Runs test is one of the prominent non-parametric tests of the random walk hypothesis (RWH). A run is defined as the sequence of consecutive changes in the return series. If the sequence is positive (negative), it is called positive (negative) run and if there are no changes in the series, a run is zero. The expected runs are the change in returns required, if a random process generates the data. If the actual runs are close to the expected number of runs, it indicates that the returns are generated by a random process. The expected number of runs (ER) is computed as

$$\mathrm{ER} = \frac{X\,(X-1) - \sum_{i=1}^{3} c_i^2}{X} \qquad \text{. . . (2)}$$

where X is the total number of runs, c_i is the number of returns changes of each category of sign (i = 1, 2, 3). The ER in equation (2) has an approximate normal distribution for large X. Hence, to test the null hypothesis, standard Z statistic can be used[4].

[4] For further discussion on runs test, see Siegel (1956).

2.1.3 Lo and MacKinlay (1988) Variance Ratio Test[5]

Lo and MacKinaly (1988) proposed the variance ratio test, which is capable of distinguishing between several interesting alternative stochastic processes. Under RWH for stock returns r_t, the variance of r_t+r_{t-1} are required to be twice the variance of r_t. Following Campbell *et al* (1997), let the ratio of the variance of two period returns, $\mathrm{r}_t(2) \equiv \mathrm{r}_t - \mathrm{r}_{t-1}$, to twice the variance of a one-period return r_t. Then variance ratio VR (2) is

$$\mathrm{VR}(2) = \frac{\mathrm{Var}\,[\mathrm{r_t}(2)]}{2\,\mathrm{Var}\,[\mathrm{r_t}]} = \frac{\mathrm{Var}\,[\mathrm{r_t}+\mathrm{r}_{t-1}]}{2\,\mathrm{Var}\,[\mathrm{r_t}]}$$

$$= \frac{2\,\mathrm{Var}\,[\mathrm{r}_t]+2\,\mathrm{Cov}\,\,[\mathrm{r_t},\mathrm{r}_{t-1}]}{2\,\mathrm{Var}\,[\mathrm{r_t}]}$$

$$\mathrm{VR}(2) = 1 + \rho(1) \qquad \ldots(3)$$

where ρ (1) is the first order autocorrelation coefficient of returns $\{\mathrm{r_t}\}$. RWH which requires zero autocorrelations holds true when VR (2) =1. The VR (2) can be extended to any number of period returns, q. Lo and MackKinaly (1988) showed that the q period variance ratio satisfies the following relation:

$$\mathrm{VR}\,(q) = \frac{\mathrm{Var}\,[\mathrm{r_t}\,(q)]}{q.\mathrm{Var}\,[\mathrm{r_t}]} = 1 + 2\sum_{k=1}^{q-1}\left(1-\frac{\mathrm{k}}{q}\right)\,\rho^{\mathrm{k}} \qquad \ldots(4)$$

where $\mathrm{r}_t(k) \equiv \mathrm{r}_t + \mathrm{r}_{t-1} + \cdots + \mathrm{r}_{t-k+1}$ and ρ (k) is the k^{th} order autocorrelation coefficient of $\{\mathrm{r}_t\}$. Equation (4) shows that at all q, VR (q) = 1. For random walk to hold, variance ratio is expected to be equal to unity. The test is based on standard asymptotic approximations. Lo-MacKinlay proposed Z (q) standard normal test statistic[6] under the null hypothesis of homoscedastic increments and VR (q) =1. However, the rejection of RWH because of heterscedasticity, which is a common feature of financial returns, is not useful for any practical

[5] A detailed discussion on the test and its empirical application can be seen in Campbell *et al* (1997).
[6] A detailed discussion on sampling distribution, size and power of the test can also be found in Lo and MacKinlay (1999)

purpose. Hence, Lo-MacKinlay constructed a heterscedastic robust test statistic Z* (q) which can be defined as

$$Z^*(q) = \frac{\text{VR}\,(q)-1}{\phi^*(q)^{1\backslash 2}} \qquad \ldots (5)$$

which follows a standard normal distribution asymptotically. Thus, according to variance ratio test, the returns process is a random walk when the variance ratio at a holding period q is expected to be unity. If it is less than unity, it implies negative autocorrelation and if it is greater than one, indicates positive autocorrelation.

2.1.4 Chow and Denning (1993) Multiple Variance Ratio Test

The variance ratio test of Lo and MacKinlay (1988) estimates individual variance ratios where one variance ratio is considered at a time, for a particular holding period (q). Empirical works examine the variance ratio statistics for several q values. The null of the random walk is rejected if test statistics are significant for some q value. Therefore, it is essentially an individual hypothesis test. The variance ratio of Lo and MacKinlay (1988) tests whether the variance ratio is equal to one for a particular holding period, whereas the RWH requires that variance ratios for all holding periods should be equal to one and the test should be conducted jointly over a number of holding periods. The sequential procedure of this test leads to size distortions and the test ignores the joint nature of random walk. To overcome this problem, Chow and Denning (1993) proposed multiple variance ratio test wherein a set of multiple variance ratios over a number of holding periods can be tested to determine whether the multiple variance ratios (over a number of holing periods) are jointly equal to one. In Lo-MacKinlay test, under the null, $\text{VR}\,(q) = 1$, but in multiple variance ratio test, $M_r = (q_i) = VR\,(q) - 1 = 0$. This can be generalized to a set of *m* variance ratio tests as

$$\{\, \text{M}_r\,(q_i) |\, i = 1{,}2 \ldots, m \,\} \qquad \ldots (6)$$

Under RWH, multiple and alternative hypotheses are as follows

$$\mathrm{H}_{0i} = \mathrm{M}_r = 0 \text{ for } i = 1, 2, \dots, m \qquad \dots (7a)$$

$$\mathrm{H}_{1i} = \mathrm{M}_r\ (q_i) \neq 0 \text{ for any } i = 1,2, \dots, m \qquad \dots (7b)$$

The null of random walk is rejected when any one or more of H_{0i} is rejected. The heteroscedastic test statistic in Chow-Denning is given as:

$$\mathrm{CD} = \sqrt{\mathrm{T}} \max\ |_{1 \leq i \leq}\ \mathrm{Z}^*\ (q_i)\ | \qquad \dots (8)$$

where $\mathrm{Z}^*\ (q_i)$ is defined as in equation (5). Chow-Denning test follows studentized maximum modulus, $\mathrm{SMM}(\alpha, m, \mathrm{T})$, distribution with m parameters and T degrees of freedom. The RWH is rejected if the value of the standardized test statistic CD is greater than the SMM critical values at chosen significance level.

2.2 Nonlinear Tests

To test the presence of nonlinear dependence, we have carried out a set of nonlinear tests to avoid sensitivity of empirical results to test employed. Before performing these tests, the linear dependence is removed from the data through fitting AR (p). The optimal lag is selected so that there is no significant LB Q statistic for residuals extracted from AR (p) model. Hence, the rejection of null for residuals implies presence of nonlinear dependence in returns.

2.2.1 McLeod-Li Test

McLeod and Li's (1983) portmanteau test of nonlinearity seeks to discover whether the squared autocorrelation function of returns is non-zero. The test statistic is

$$Q_{(m)} = \frac{n(n+2)}{n-k} \sum_{k-1}^{m} r_a^2(k) \qquad \dots (9)$$

$$r_a^2(k) = \frac{\sum_{t-k+1}^{m} e_t^2 e_{t-k}^2}{\sum_{t-1}^{n} e_t^2}\ k = 0,1, \dots n-1$$

where r_a^2 is the autocorrelation of the squared residuals and e_t^2 is obtained after fitting appropriate AR (p). McLeod-Li tests for 2[nd] order nonlinear dependence.

2.2.2 Tsay Test

Tsay (1986) proposed a test to detect the quadratic serial dependence in the data. Suppose *K*=k (k-1) / 2 column vector contains all the possible cross products of the form r_{t-1} r_{t-j} where ϵ [i, k]. Thus, $v_{t,1} = r_{t-1}^2$; $v_2 = r_{t-1}, r_{t-2}$; $v_{t,3} = r_{t-1}r_{t-3}$; $v_{tK+1} = r_{t-2}r_{t-3}$; $v_{t,k+2} = r_{t-2}r_{t-4}$ ...and $v_{t,k} = r_{t-k}^2$. Further, Let $\hat{v}_{t,i}$ denote the projection of $v_{t,i}$ on $r_{t-1} \dots, r_{t-k}$, on the subspace orthogonal to $r_{t-1}, \dots\ r_{t-k}$ (the residuals from a regression of $v_{t,i}$ on $r_{t-1}, \dots, r_{t-k}$. Using following regression, the parameters $\gamma_1, \dots\ \gamma_k$ are estimated:

$$r_{t-1} = \gamma_0 + \sum_{i=1}^{k} \gamma_i \hat{v}_{t,i} + \varepsilon_t \qquad \dots (10)$$

The Tsay F statistic is for testing the null hypothesis that $\gamma_1, \dots\ \gamma_k$ are all zero.

2.2.3 Engle (1982) Test

Engle (1982) proposed Lagrange Multiplier test to detect ARCH distributive. The test statistic based on R2 of an auxiliary regression, is defined as

$$r_t^2 = \alpha_0 + \sum_{i=1}^{M} \alpha_i r_{t-i}^2 + \varepsilon_t \qquad \dots (11)$$

When the sample size is *n*, under the null hypothesis of a linear generating mechanism for $\{e_t\}$, the test statistic NR^2 for this regression is asymptotically distributed, χ_p^2.

2.2.4 Hinich bicorrelation Test

The portmanteau bicorrelation test of Hinich (1996) is a third order extension of the standard correlation tests for white noise. The null hypothesis is that the transformed data $\{r_t\}$ are realizations of a stationary pure noise process that has zero bicorrelation (H). Thus, under the null, bicorrelations (H) are expected to be equal to zero. The alternative hypothesis is that the process has some non-zero bicorrelations (third order nonlinear dependence).

$$H = \sum_{S=2}^{L} \sum_{r=1}^{S-1} [G^2(r-s)/(T-S)] \sim\ x^2(L-1)\left(\frac{L}{2}\right) \qquad \dots (12)$$

where $G(r,s) = \sum_{k=1}^{T-S}[Z(t_k)Z(t_k + r)(t_k + s)]$. Z ($t_k$) are standard observations at time t=k, and $L=T^c$ with 0<c<0.5[7].

2.2.5 BDS Test

Brock *et al* (1996) developed a portmanteau test for time-based dependence in a series, which is popularly known as BDS (named after its authors) [8]. The BDS test uses the correlation dimension of Grassberger and Procaccia (1983). To perform the test for a sample of n observations $\{x_1,..,x_n\}$, an embedding dimension *m*, and a distance ε, the correlation integral $C_m(n, \varepsilon)$ is estimated by

$$C_m(n, \varepsilon) = \frac{2}{(n-m)\,(n-m+1)} \sum_{S=1}^{n-m} \sum_{t=S+1}^{n-m+1} I_m\,(x_s,\, x_t\,, \varepsilon). \qquad ...(13)$$

where *n* is sample size, *m* is embedding dimension and ε is the maximum difference between pairs of observations counted in estimating the correlation integral. The test statistic is given the following equation:

$$W_m(\varepsilon) = \sqrt{\frac{n}{\hat{V}_m}}\,(C_m(n,\varepsilon) - C_1(n,\varepsilon)^m) \qquad ...(14)$$

The BDS considers the random variable $\sqrt{n}(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m$ which, for an *iid* process converges to the normal distribution as *n* increases. It has power against a variety of possible alternative specifications like nonlinear dependence and chaos. The BDS statistic is commonly estimated at different *m*, and ε.

3. Empirical Results

This section discusses the empirical results of both linear and nonlinear tests carried out in the present paper. Table 1 reports the descriptive statistics for Sensex and Nifty returns. The mean returns are positive during the full sample period and Sensex average returns were highest during 1991-93 while Nifty registered highest average returns in subsample 2003-05. The

[7] Hinich and Patterson in their unpublished work of 1995 recommend c=0.4. The same is followed here.
[8] Taylor (2005) presents an excellent discussion on the test and its power properties.

standard deviation of Nifty returns is greater than the Sensex. The former witnessed higher volatility during 2006-08 while the latter exhibited relatively higher volatility during 2000-2002 and 2006-08, the periods of financial and economic crises. The skewness is negative for the full sample and the majority of subsamples implying that the returns are flatter to the left compared to the normal distribution. Moreover, it indicates that the extreme negative returns have greater magnitude than the positive. The significant kurtosis indicates that return distribution has sharp peaks compared to a normal distribution. Further, the significant Jarque and Bera (1980) statistic confirm that index returns are non- normally distributed.

The present study employs Ljung-Box test to check whether all autocorrelations are simultaneously equal to zero. Table 2 documents the autocorrelation test results. The results show that the full sample of both Sensex and Nifty possess autocorrelations that are significant indicating dependence in stock returns. The sub-sample results show that returns possess autocorrelations in the first two sub-periods. It is interesting to find that the 1997-1999, 2000-2002 sub-periods are characterized by independence of returns followed by significant autocorrelations in subsample 2003-2005. Nevertheless, the last three subsamples do not possess autocorrelations. The results for Nifty indicate that the first four subsamples have first order autocorrelation with the exception during sub-period 1997-1999 and thus suggest the possibility of predictability of returns. Similar to Sensex, the 2006-2008, 2009-2011 and 2012-2013 show no autocorrelations suggesting independence of returns. The results from runs tests are presented in the last column of Table 2. The statistically significant negative values of Z test for both Sensex and Nifty indicate positive correlation. The results show that during the first five subsamples, the null of the random walk is rejected with the exception in 1997-1999, where Z

Table 1 Descriptive Statistics

Sample Period	Mean	Minimum	Maximum	S.D	Skewness	Kurtosis	Jaqua-Bera
			Sensex				
Full sample	0.000553	-0.136	0.159	0.017	-0.042	5.893	7780.03
Jan 1991 – Dec 1993	0.001988	-0.136	0.123	0.024	-0.047	4.624	541.93
Jan 1994 - Dec 1996	-0.000116	-0.046	0.056	0.014	0.454	1.229	68.16
Jan 1997 – Dec 1999	0.000656	-0.086	0.073	0.018	-0.086	2.091	135.45
Jan 2000 – Dec 2002	-0.000525	-0.074	0.071	0.017	-0.338	2.165	160.65
Jan 2003 – Dec 2005	0.001348	-0.118	0.079	0.013	-1.139	11.120	4075.26
Jan 2006 – Dec 2008	0.000035	-0.116	0.079	0.021	-0.344	2.584	222.00
Jan 2009 – Dec 2011	0.000635	-0.075	0.159	0.016	1.291	14.567	6766.81
Jan 2012- Dec 2013	0.000699	-0.027	0.026	0.009	0.077	0.580	5.014
			Nifty				
Full sample	0.00035	-0.130	0.163	0.0162	-0.122	6.428	8262.46
Jan 1994 - Dec 1996	-0.0002	-0.043	0.054	0.0139	0.498	1.456	92.78
Jan 1997 – Dec 1999	0.0006	-0.088	0.099	0.0098	0.009	3.680	422.17
Jan 2000 – Dec 2002	-0.0004	-0.072	0.072	0.0160	-0.244	2.652	227.11
Jan 2003 – Dec 2005	0.0012	-0.130	0.079	0.0139	-1.407	12.870	5488.81
Jan 2006 – Dec 2008	0.0001	-0.130	0.067	0.0209	-0.530	3.298	372.82
Jan 2009 – Dec 2011	0.0006	-0.063	0.163	0.0156	1.403	15.912	8078.16
Jan 2012 – April 2013	0.0007	-0.027	0.027	0.0091	0.079	0.643	6.09

Table 2 LB Q and Run Tests Statistics

Sample Periods	LB (5)	LB (15)	LB (20)	Runs Z Statistics
		Sensex		
Full Sample	-0.001 (46.45)*	0.024 (75.99)*	-0.023 (96.84)*	-6.385*
Jan 1991 – Dec 1993	0.086 (21.04)*	0.113 (52.22)*	0.055 (60.94)*	- 3.528*
Jan 1994 - Dec 1996	0.015 (38.39)*	0.011 (48.20)*	-0.052 (50.89)*	- 4.236
Jan 1997 – Dec 1999	-0.050 (3.73)	-0.020 (17.04)	-0.046 (22.41)	-1.842
Jan 2000 – Dec 2002	-0.022 (6.34)	0.006 (14.42)	-0.094 (31.77)**	- 2.611*
Jan 2003 – Dec 2005	-0.032 (26.58)*	-0.056 (35.45)*	0.010 (44.28)*	- 2.358*
Jan 2006 – Dec 2008	-0.017 (7.60)	0.011 (15.23)	-0.049	- 1.3356
Jan 2009 – Dec - 2011	-0.055 (6.65)	0.002 (17.41)	-0.081 (31.47)**	- 0.439
Jan 2012 – April 2013	-0.008 (2.15)	0.009 (12.78)	0.024 (22.54)	- 0.929
		Nifty		
Full Sample	-0.008 (34.69)*	0.001 (60.71)*	-0.042 (91.60)*	- 5.765*
Jan 1994 - Dec 1996	0.030 (44.35)*	0.003 (57.73)*	-0.020 (59.53)*	- 5.161*
Jan 1997 – Dec 1999	0.002 (0.267)	-0.016 (14.35)	0.009 (23.68)	- 0.052
Jan 2000 – Dec 2002	0.016 (12.74)**	0.013 21.02	-0.107 38.90*	- 2.962*
Jan 2003 – Dec 2005	-0.037 37.46*	-0.059 55.30*	0.013 61.54*	- 2.270**
Jan 2006 – Dec 2008	-0.011 4.81	0.026 24.02	-0.066 31.58**	- 1.105
Jan 2009 – Dec - 2011	-0.060 4.98	-0.006 16.93	-0.006 29.14	0.0367
Jan 2012 – April 2013	0.000 2.69	0.005 14.66	0.017 21.51	-0.874

The autocorrelation coefficient followed by The Ljung-Box (LB) Q statistics in parenthesis are given in the table at lags 5, 15 and 20 for the full sample and subsample period. The null of LB is zero autocorrelation. The last column furnishes the Runs Z statistics. * and * denote the significance level at 1 % and 5 % respectively.

value is insignificant. Similar to Ljung-Box test results, the runs test results for the last three subsamples show no evidence autocorrelation. It is notable that no significant autocorrelations were found during those periods in which the major crashes such as East Asian financial crisis, dotcom bubble burst, and sub-prime mortgage crisis occurred. These findings are consistent with Kim *et al* (2011) who observed no predictability during stock market crashes (1929 and 1987). The autocorrelation and runs test results indicate that the Indian stock market is switching between efficiency and inefficiency. In other words, these results support the view that Indian stock market is adaptive.

Furthermore, Table 3 reports Lo and MacKinlay variance ratios and corresponding heteroscedasticity robust test statistic at various investment horizons like 2, 4, 8, and 16[9]. The variance ratios at all the chosen investment horizons (q) for Sensex and Nifty during the full sample are greater than unity and statistically significant at 1 percent significance level, indicating returns do not follow a random walk. Nevertheless, it is interesting to note that no subsample exhibit significant variance ratio statistic at any investment horizon indicating that returns are independent. The sequential procedure of Lo and MacKinlay (1988) test sometime leads to size distortions and the test ignores the joint nature of random walk. To overcome this problem, Chow and Denning (1993) multiple variance ratio test is carried out and the results are documented in the last column of Table 3. The Chow-Denning test statistic indicate predictability of stock returns based on past memory returns in India by significantly rejecting null of random walk over the whole sample. However, every subsample provides evidence of the independence of returns. The individual and multiple variance ratio results suggest that the

[9] The volatility is time varying and therefore rejection of null of variance ratio equal to unity due to conditional heteroscedasticity is not of much interest and less relevant for the practical applications. Hence, we reported only heteroscedastic robust test statistic.

Table 3 Variance Ratio Test Statistics

Sample Periods	Lo-MacKinlay Variance Ratios for Investment Horizons (*q*)				Chow and Denning Statistic
	2	4	8	16	
Sensex					
Full Sample	1.08* (3.767)	1.12* (2.878)	1.12*** (1.868)	1.19** (2.071)	3.767**
Jan 1991 – Dec 1993	1.11 (1.066)	1.20 (1.083)	1.26 (0.910)	1.42 (1.001)	1.066
Jan 1994 - Dec 1996	1.21 (0.772)	1.27 (0.567)	1.32 (0.424)	1.21 (0.196)	0.772
Jan 1997 – Dec 1999	1.04 (0.291)	1.08 (0.292)	1.03*** (0.082)	1.06 (0.094)	0.291
Jan 2000 – Dec 2002	1.06 (0.391)	1.09 (0.298)	1.10 (0.211)	1.11 (0.163)	0.391
Jan 2003 – Dec 2005	1.08 (0.273)	1.02 (0.052)	1.08 (0.104)	1.15 (0.129)	0.271
Jan 2006 – Dec 2008	1.07 (0.653)	1.07 (0.346)	0.985 (-0.045)	1.05 (0.124)	0.653
Jan 2009 – Dec 2011	1.06 (0.319)	1.06 (0.172)	1.01 (0.022)	1.09 (0.117)	0.319
Jan 2012 – April 2013	0.98 (-0.01)	1.06 (0.023)	1.10 (0.024)	1.10 (0.018)	0.012
Nifty					
Full Sample	1.07* (3.180)	1.08*** (1.896)	1.06 (1.071)	1.10 (1.121)	3.180*
Jan 1994 - Dec 1996	1.23 (1.055)	1.31 (0.789)	1.40 (0.673)	1.25 (0.304)	1.055
Jan 1997 – Dec 1999	1.00 (0.003)	0.99 (-0.005)	0.96 (-0.107)	0.96 (-0.068)	0.003
Jan 2000 – Dec 2002	1.09 (0.602)	1.08 (0.284)	1.11 (0.260)	1.15 (0.252)	0.602
Jan 2003 – Dec 2005	1.11 (0.586)	1.06 (0.183)	1.12 (0.218)	1.16 (0.203)	0.587
Jan 2006 – Dec 2008	1.06 (0.677)	1.06 (0.395)	0.99 (-0.015)	1.07 (0.216)	0.677
Jan 2009 – Dec - 2011	1.04 (0.276)	1.05 (0.172)	1.00* (0.002)	1.07 (0.112)	0.288
Jan 2012 – April 2013	0.97 (-0.021)	1.06** (0.032)	1.10** (0.035)	1.12** (0.029)	0.021

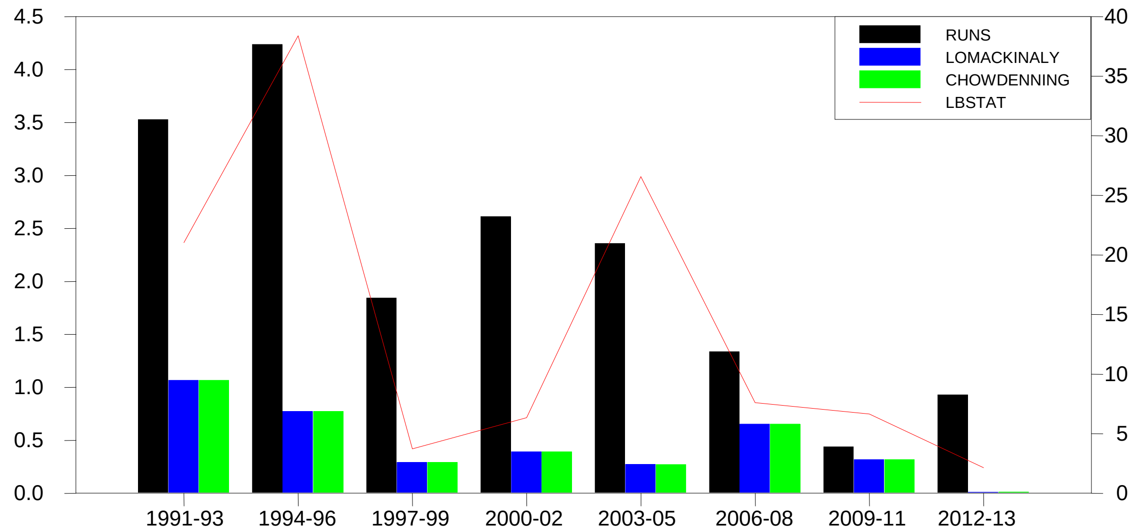
Note: The Lo-MacKinlay variance ratios VR (*q*) are reported in the main rows and variance test statistic Z * (*q*) for heteroscedastic robust test statistics are given in parentheses. Under the null of random walk, the variance ratio value is expected to equal one. Chow-Denning heteroscedastic statistics are presented in the last column and the critical value is 2.49. *, ** and *** denote significance at 1 %, 5% and 10 % respectively

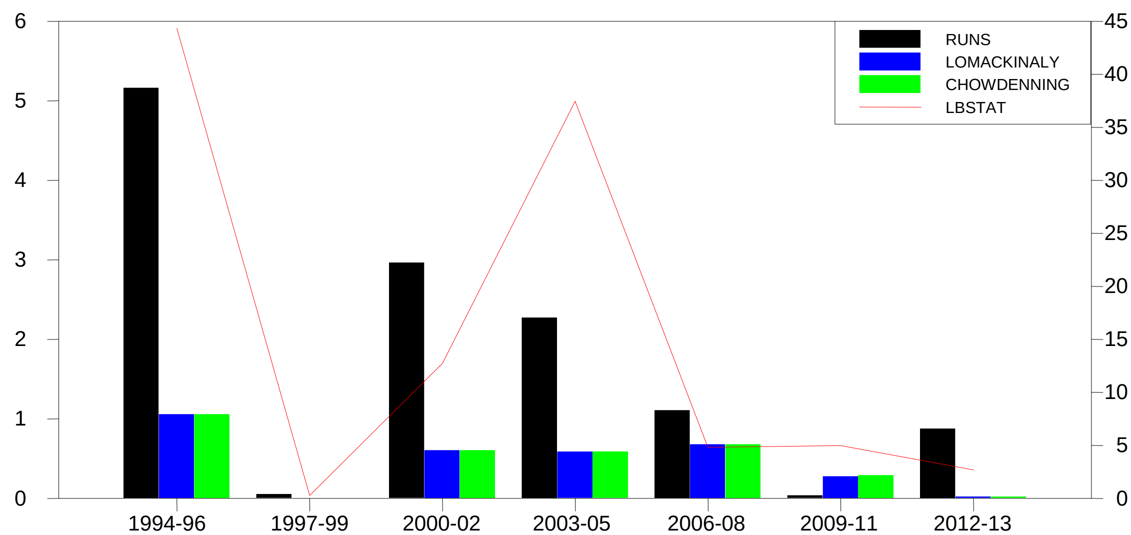
Indian market is largely efficient surrounded by very brief periods of predictability which disappear as information quickly begins to reflect in returns and market moves towards efficiency again.

The trends in linear test statistics are presented in Fig. 1 to examine the magnitude of linear dependence during the sample period. For Sensex, the results show that LB statistics witness sharp upward and downward spikes during the sample period. The test statistics were highest during 1994-1996 and 2003-2005. It is interesting to observe that the LB Q statistics started moving downward from 2006 including the periods of sub-prime mortgage crisis and global economic meltdown of 2008. The trends in runs statistics exhibit similar patterns. The Lo-MacKinlay and Chow-Denning statistics show that the magnitude of linear dependence is highest during the first two subsamples, 1994-1996, 1997-1999. Thereafter, the trend in test statistics is set downward, and values are insignificant indicating no predictability of returns based on past returns. The trends in magnitude of linear dependence in case of Nifty are not different from Sensex. The linear test results presented in Fig. 1 indicate highest linear dependence in Nifty returns during subsample 1994-1996 and 2003-2006. In the rest of the subsamples, the values are very low showing no autocorrelation or linear dependence in Nifty returns. Strikingly, linear test statistics are lowest and insignificant during 1997-199 and 2006-2008, the periods of Asian financial crash and sub-prime mortgage crisis followed by a global recession respectively. Overall, the inference drawn from the Fig. 1 is that the magnitude of linear dependence has fallen over the period. In other words, the results support that the Indian stock market has become efficient after 2002. It may be because of the fact that NSE has brought several changes in market microstructure and trading practices which were later followed by BSE. It appears that these changes along with financial sector reforms and regulatory measure of

Securities and Exchange Board of India (SEBI) have positively influenced the efficiency in the market.

Fig. 1 Trends in Linear Test Statistics





The linear tests such as autocorrelation, variance ratio, and runs tests are not capable of capturing nonlinear patterns in the return series. The failure to reject linear dependence is not sufficient to prove independence in view of the non-normality of the series (Hsieh, 1989) and does not necessarily imply independence (Granger and Anderson, 1978). The presence of nonlinearity provides opportunities for market participants make excess profits. The use of linear models in such conditions may give the wrong inference of unpredictability. Moreover, the presence of nonlinearity in stock returns contradicts EMH. In this study, we employed a set of nonlinear tests to investigate the presence of nonlinear dependence in Sensex and Nifty index returns. Before performing these tests, linear dependence is removed by fitting appropriate AR (ρ) model so that any remaining dependence would be rendered nonlinear. We have employed LB test again on residuals extracted after filtering by fitting an appropriate AR (ρ) and LB statistics are reported in Table 4. The results show no autocorrelation up to lag 20 for each subsample of Sensex and Nifty.

The McLoed-Li test is implemented on AR (ρ) filtered residuals and Table 4 documents corresponding statistics. The tests show that each subsample of Sensex and Nifty has a nonlinear dependency at 1 per cent significance level with the exception during 2012-13, and 2009-2013 in case of Sensex and Nifty respectively. This indicates that Indian stock market is inefficient during these sample periods and over the whole sample. Further, Table 5 presents the Tsay and Engle LM test results at lags 5, 15 and 20. The results reveal that after filtering of data by AR (ρ), the Sensex and Nifty returns show strong evidence of nonlinear behavior for both the full sample and subsamples. Similar to McLeod-Li results, the Tsay and Engle LM tests could not reject absence of nonlinear dependence in the last subsample (2012-13). Overall, the results presented in Table 4 and 5 show a significant presence of nonlinarity in returns. This implies that Indian stock market was not weakly efficient throughout the period.

Table 4 McLeod Li Test Statistics

Sample Periods	AR (ρ)	LB (5)	LB (15)	LB (20)	McLeod-Li Statistic		
					Lag 5	Lag 15	Lag 20
Sensex							
Full sample	9	0.043 (1.000)	0.748 (1.000)	26.32 (0.155)	988.6* (0.000)	2130.1* (0.000)	2415.5* (0.000)
Jan 1991 – Dec 1993	7	0.196 (0.999)	24.06 (0.064)	29.57 (0.077)	81.7* (0.000)	238.0* (0.000)	255.3* (0.000)
Jan 1994 - Dec 1996	2	4.745 (0.447)	16.94 (0.322)	19.14 (0.512)	47.17* (0.000)	97.49* (0.000)	130.53* (0.000)
Jan 1997 – Dec 1999	1	3.64 (0.602)	16.86 (0.327)	22.38 (0.320)	30.19* (0.000)	41.84* (0.000)	52.99* (0.000)
Jan 2000 – Dec 2002	2	3.161 (0.675)	11.00 (0.752)	26.48 (0.150)	187.69* (0.000)	296.07* (0.000)	329.56* (0.000)
Jan 2003 – Dec 2005	2	8.673 (0.122)	20.459 (0.155)	23.306 (0.274)	245.29* (0.000)	263.26* (0.000)	264.19* (0.000)
Jan 2006 – Dec 2008	2	2.349 (0.798)	18.209 (0.251)	23.168 (0.280)	277.27* (0.000)	590.73* (0.000)	671.05* (0.000)
Jan 2009 – Dec - 2011	2	6.263 (0.281)	18.81 (0.222)	23.67 (0.296)	4.712 (0.451)	29.28** (0.014)	33.42** (0.030)
Jan 2012 – April 2013	0	2.152 (0.827)	12.788 (0.618)	22.546 (0.311)	1.550 (0.907)	15.00 (0.451)	27.79 (0.114)
Nifty							
Full sample	11	0.028 (1.000)	6.371 (0.972)	26.939 (0.137)	550.20* (0.000)	964.60* (0.000)	1066.23* (0.000)
Jan 1994 - Dec 1996	2	5.813 (0.324)	19.919 (0.175)	21.824 (0.350)	69.38* (0.000)	154.97* (0.000)	185.82* (0.000)
Jan 1997 – Dec 1999	0	0.267 (0.998)	14.356 (0.498)	23.686 (0.256)	23.72* (0.000)	28.13** (0.020)	49.47* (0.000)
Jan 2000 – Dec 2002	2	1.429 (0.921)	7.764 (0.932)	22.700 (0.303)	108.87* (0.000)	199.44* (0.000)	220.53* (0.000)
Jan 2003 – Dec 2005	2	8.715 (0.157)	21.42 (0.321)	28.444 (0.099)	286.24* (0.000)	310.20* (0.000)	311.07* (0.000)
Jan 2006 – Dec 2008	2	1.593 (0.902)	19.37 (0.197)	26.913 (0.137)	232.57* (0.000)	441.67* (0.000)	489.24* (0.000)
Jan 2009 – Dec - 2011	2	3.379 (0.641)	14.305 (0.502)	26.676 (0.144)	2.177 (0.824)	18.701 (0.227)	22.491 (0.314)
Jan 2012 – April 2013	0	2.697 (0.746)	14.663 (0.475)	21.516 (0.367)	2.667 (0.751)	16.101 (0.375)	30.169*** (0.067)

The autocorrelation coefficient followed by The Ljung-Box (LB) Q statistics in parenthesis are given in the table at lags 5, 15 and 20 for the full sample and subsample period. *, ** and *** denote significance at 1%, 5% and 10 % respectively.

Table 5 Tsay, Engle LM and H Statistics

Sample Period	AR (ρ)	Tsay F Statistic			Engle LM Statistic			H Statistic
		Lag 5	Lag 15	Lag 20	Lag 5	Lag 15	Lag 20	
Sensex								
Full sample	9	7.862* (0.000)	3.613* (0.000)	3.039* (0.000)	564.1* (0.000)	729.5* (0.000)	758.2* (0.000)	3760.9* (0.000)
Jan 1991 – Dec 1993	7	2.837* (0.000)	1.907* (0.000)	1.786* (0.000)	54.8* (0.000)	101.2* (0.000)	110.5* (0.000)	405.6* (0.000)
Jan 1994 - Dec 1996	2	1.858* (0.000)	1.273** (0.041)	1.282** (0.016)	32.4* (0.000)	50.5* (0.000)	74.9* (0.000)	139.7* (0.000)
Jan 1997 – Dec 1999	1	2.436* (0.001)	1.686* (0.000)	1.457* (0.000)	28.86* (0.000)	37.5* (0.001)	47.7* (0.005)	183.9* (0.000)
Jan 2000 – Dec 2002	2	2.396* (0.002)	2.433* (0.000)	2.168* (0.000)	110.67* (0.000)	138.8* (0.000)	148.9* (0.000)	364.8* (0.000)
Jan 2003 – Dec 2005	2	6.609* (0.000)	2.257* (0.000)	1.910* (0.000)	268.96* (0.000)	272.2* (0.000)	272.3* (0.000)	721.7* (0.000)
Jan 2006 – Dec 2008	2	4.734* (0.000)	2.746* (0.000)	2.667* (0.000)	153.7* (0.000)	179.4* (0.000)	181.7* (0.000)	680.9* (0.000)
Jan 2009 – Dec - 2011	1	1.24 (0.229)	2.50* (0.000)	2.483* (0.000)	4.9 (0.495)	22.8 (0.088)	24.3 (0.231)	242.9* (0.000)
Jan 2012 – April 2013	0	0.560 (0.903)	1.558* (0.003)	1.073 (0.359)	1.6 (0.911)	13.3 (0.576)	25.8 (0.172)	52.8 (0.198)
Nifty								
Full sample	9	6.240* (0.000)	2.877* (0.000)	2.427* (0.000)	352.20* (0.000)	425.36 (0.000)	437.38* (0.000)	1848.41* (0.000)
Jan 1994 - Dec 1996	2	1.509 (0.095)	1.583* (0.000)	1.436* (0.000)	50.21* (0.000)	77.758 (0.000)	92.62* (0.000)	158.67* (0.000)
Jan 1997 – Dec 1999	0	2.842* (0.000)	1.687* (0.000)	1.295** (0.011)	24.21* (0.000)	27.85** (0.022)	51.658* (0.000)	157.77* (0.000)
Jan 2000 – Dec 2002	2	1.852** (0.024)	2.173* (0.000)	1.949* (0.000)	79.97* (0.000)	126.46* (0.000)	130.54* (0.000)	380.80* (0.000)
Jan 2003 – Dec 2005	2	6.757* (0.000)	2.413* (0.000)	1.985* (0.000)	315.46* (0.000)	320.34* (0.000)	321.86* (0.000)	799.69* (0.000)
Jan 2006 – Dec 2008	2	5.583* (0.000)	2.705* (0.000)	2.459* (0.000)	125.40* (0.000)	152.41* (0.000)	158.98* (0.000)	663.08* (0.000)
Jan 2009 – Dec - 2011	2	0.873 (0.593)	2.313* (0.000)	2.268* (0.000)	2.023 (0.845)	15.292 (0.430)	16.87 (0.661)	195.63* (0.000)
Jan 2012 – April 2013	2	0.489 (0.945)	1.577* (0.003)	1.181 (0.193)	2.931 (0.710)	14.672 (0.475)	27.786 (0.114)	56.255 (0.121)

*,** denote 1 % and 5 % significance level.

The Hinich bicorrelation (H) tests the null of pure noise. The H statistics presented in Table 5 reveal that with the exception of subsample 2012-2013, the null of pure noise is clearly rejected for Sensex and Nifty returns at 1 percent level of significance. The inference drawn is that nonlinearity characterizes the Indian stock returns and hence returns are predictable . In short, the results documented in Table 5 show strong evidence of nonlinear dependence in returns indicating Indian stock market is inefficient during the full sample period and sub-periods as well. Finally, the BDS test is performed at various embedded dimensions (m) like 2, 4, and 8 and 10 at various distances (ε) like 0.75s, 1.0s, 1.25s and 1.50s where s denotes standard deviations of the return. It is clear from the BDS statistics in Table 6 that all the subsamples and full sample reject the null for both the indices. The rejection for residuals from AR (ρ) indicates presence of nonlinear dependence in the Sensex and Nifty returns series implying the possible predictability of future returns using the history of returns. This invalidates EMH in case of Indian stock market.

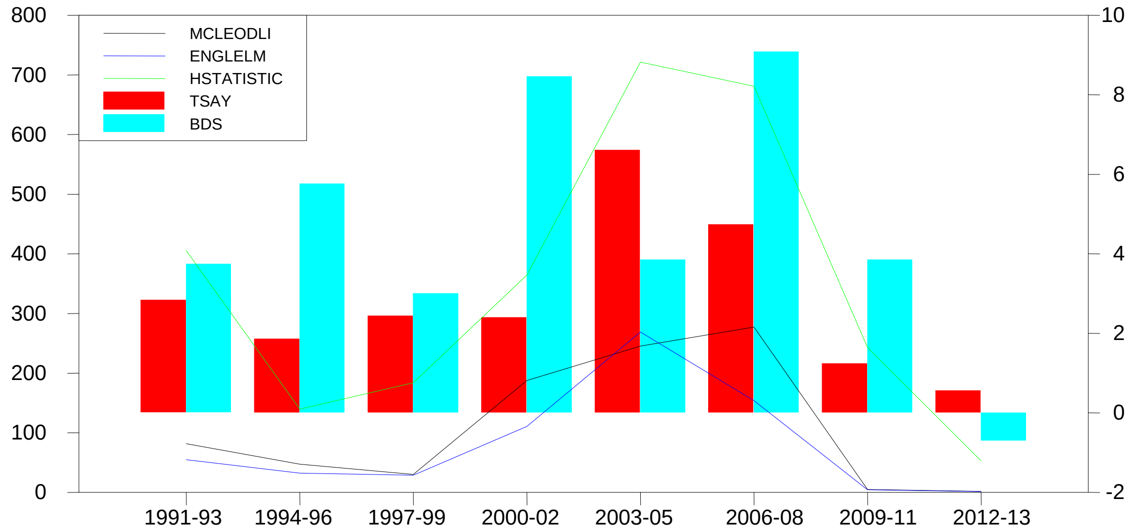
To comprehend the magnitude of nonlinear dependence, Fig. 2 plots the nonlinear test statistics. The McLeod-Li results show stronger presence of nonlinear dependence in Sensex and Nifty returns during subsamples 2003-2005 and 2006-2008. Again, the trends in Engle LM, Tsay, H and BDS test statistics are low indicating lesser magnitude of nonlinear dependency again both in Sensex and Nifty returns up to 2000 and thereafter returns exhibit increasing nonlinear tendency reaching peak during subsample, 2006-2008. However, in post 2008 subsample, all the test statistics are less significant suggesting weaker presence of nonlinear dependence in returns.

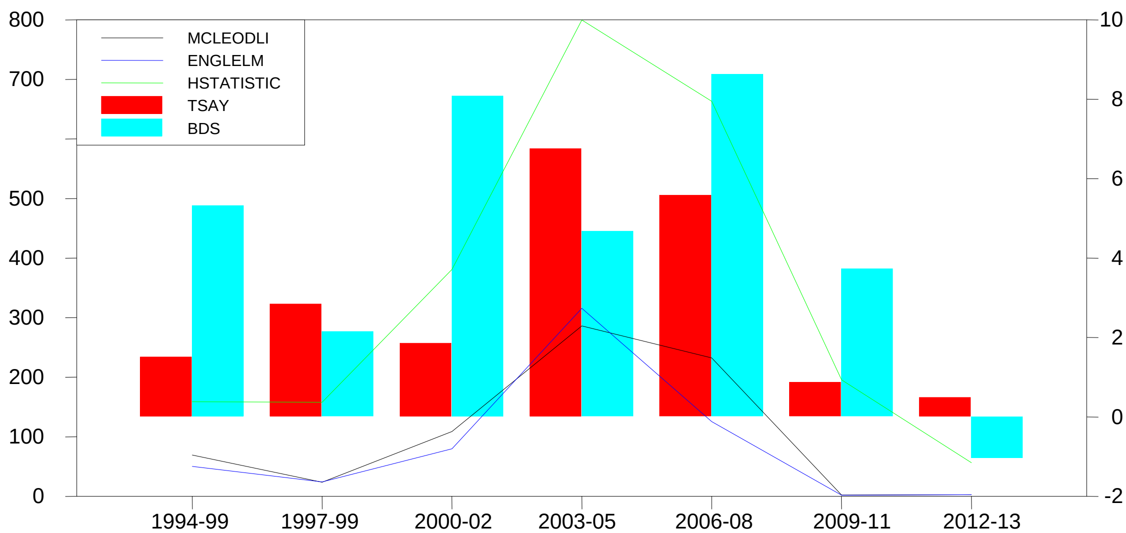
Table 6 BDS Test Statistics

Sample Period	AR (ρ)	m=2, ε = 0.75s	m=4, ε = 1.0s	m=8, ε =1.25 *S*	m=10, ε=1.50s
Sensex					
Full sample	9	17.65* (0.000)	27.88* (0.000)	42.94*(0.000)	44.24* (0.000)
Jan 1991 – Dec 1993	7	3.74* (0.000)	4.42*(0.000)	6.33*(0.000)	7.40*(0.000)
Jan 1994 - Dec 1996	2	5.76* (0.000)	8.24* (0.000)	11.66* (0.000)	12.21*(0.000)
Jan 1997 – Dec 1999	1	3.00* (0.002)	4.52* (0.000)	6.30*(0.000)	6.95* (0.000)
Jan 2000 – Dec 2002	2	8.46*(0.000)	13.08*(0.000)	18.11*(0.000)	19.20*(0.000)
Jan 2003 – Dec 2005	2	3.85* (0.000)	5.60* (0.000)	9.01*(0.000)	9.77* (0.000)
Jan 2006 – Dec 2008	2	9.08* (0.000)	14.26*(0.000)	24.40*(0.000)	23.56*(0.000)
Jan 2009 – Dec - 2011	1	3.85* (0.000)	7.40*(0.000)	12.98* (0.000)	14.11* (0.000)
Jan 2012 – April 2013	0	-0.71* (0.474)	0.306* (0.759)	1.893* (0.058)	2.288* (0.022)
Nifty					
Full sample	11	15.15* (0.000)	23.89 (0.000)	35.94 (0.000)	37.65 (0.000)
Jan 1994 - Dec 1996	2	5.322* (0.000)	8.534* (0.000)	11.33* (0.000)	11.73* (0.000)
Jan 1997 – Dec 1999	0	2.149* (0.031)	4.081* (0.000)	5.351* (0.000)	5.808* (0.000)
Jan 2000 – Dec 2002	2	8.08* (0.000)	12.14* (0.000)	15.28* (0.000)	15.59* (0.000)
Jan 2003 – Dec 2005	2	4.67* (0.000)	6.43* (0.000)	9.68* (0.000)	10.89* (0.000)
Jan 2006 – Dec 2008	2	8.63* (0.000)	13.89* (0.000)	23.71* (0.000)	22.49* (0.000)
Jan 2009 – Dec - 2011	2	3.73* (0.000)	6.61* (0.000)	12.02* (0.000)	12.97* (0.000)
Jan 2012 – April 2013	0	-1.05 (0.292)	0.288 (0.772)	1.732 (0.083)	2.905 (0.004)

Here, '*m*' and '*ε*' denote the embedding dimension and distance, respectively and 'ε' equal to various multiples (0.75, 1, 1.25 and 1.5) of standard deviation (*s*) of the data. The value in the first row of each cell is a BDS test statistic followed by the corresponding p-value in parentheses. The asymptotic null distribution of test statistics is N (0.1). Asterisked values indicate 1 % level of significance.

Fig. 2 Trends in Nonlinear Test Statistics





The present evidence of the strong presence of nonlinear dependence throughout the sample, and highest during periods financial crashes are consistent with the findings of Urquhart and Hudson (2013) who found similar evidence in the case of the US market. The inference from Fig. 2 is that during the sample period of the study, there has been increasing presence of nonlinear dependence with a sign of the declining magnitude of nonlinear dependence in Indian stock returns from 2009. The subsample 2006-2008, which possess strong pockets of nonlinear dependence is associated with sub-prime mortgage and global financial crisis. Overall, there is strong evidence of nonlinearity throughout the sample period in Indian market. Although we find evidence of an increasing nonlinear dependence, it is tapering in most recent subsamples.

5. Summary and conclusion

The present paper has investigated the adaptive market hypothesis (AMH) in emerging markets like India. To validate the issue empirically, we employed linear and nonlinear tests over the whole sample from 1991 to 2013 and on subsamples of two years each. The linear test LB Q and runs test results indicate a cyclical pattern in autocorrelations suggesting that the Indian stock market switched between periods of efficiency and inefficiency. The variance ratio tests find dependence only during the full sample period and independence of returns in each subsample. The findings also suggest unpredictability of returns during crisis periods. This shows that Indian stock market is efficient barring few brief periods of predictability, which quickly disappear as information starts reflecting in prices.

The failure in rejecting linear dependence is not sufficient to prove independence because of possibility of presence of nonlinearity in returns, which indicate predictability and consequent abnormal profits to the agents. To test such possibilities, we employed a set of nonlinear tests. The findings from each of the tests suggest that there is a strong presence of nonlinear dependence in Indian stock returns implying possible predictability of returns and consequent excess returns. Moreover, the results have shown that there was a strong presence of nonlinear dependence during periods of crisis in 1997-99 and 2006-2008 thus suggesting better predictability of returns during periods of crashes. The present evidence of nonlinearity in returns straight away reject the efficient market hypothesis in the case of India.

The findings of the present study do not suggest that Indian stock market is not fully adaptive, as it has not gone through at least three different stages of dependency required under AMH framework. However, linear test results indicate that Indian stock market has gone through periods of efficiency and inefficiency and, the magnitude of nonlinear dependence has declined in recent periods which is suffice it to conclude that Indian stock market is in the first stage of AMH. This implies that the reforms initiated have not fully brought the desired results. The evidence necessitates active portfolio management for generating excess returns. In light of the nonlinear dependence in returns, it is useful to use nonlinear methods for better forecasts. The present finding of an increased possibility of predictability during crashes call for appropriate policy measure to make the market immune to the ill effects of external events.

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