Chapter 2
Random Walk Characteristics of Stock Returns

Abstract This chapter studies the behavior of stock returns in India. For this purpose, data from 1997 to 2010 of 14 indices traded on the National stock exchange (NSE) and Bombay stock exchange (BSE) are used and several parametric and non-parametric methods are employed to empirically test the random walk characteristics of stock returns and examine the weak form efficiency of the Indian stock market. The results from parametric tests are mixed and validity of random walk hypothesis (RWH) is suggested only for large cap and high liquid indices traded on the BSE. However, the same is not true in the case of NSE index returns. The non-parametric tests resoundingly reject the null of random walk for the chosen indices. The results broadly suggest non-random walk behavior of stock returns and invalidate the weak form efficiency in case of India. The evidence of dependence in stock returns call for appropriate regulatory and policy changes to ensure further dissemination of information and quick and correct price aggregation in the market.

Keywords Random walk · Market efficiency · Weak form of efficiency · Stochastic process · Abnormal returns · Variance ratio · Autocorrelation · Serial dependence

2.1 Introduction

The behavior of stock returns has been extensively debated over the years. Researchers have examined the efficient market hypothesis (EMH) and random walk characterization of returns and alternatives to random walk. In an informationally efficient market, current prices quickly absorbs information and hence such a mechanism does not provide scope for an investor to make abnormal returns (Fama 1970). In respect of empirical evidence, earlier studies have found evidence in favor of random walk hypothesis (RWH) (Working 1960; Fama 1965;

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Niederhoffer and Osborne 1966). Later studies however, documented mean reversion tendency in stock returns (Jennergren and Korsvold 1974; Solnik 1973; Keim and Stambaugh 1986; Jagadeesh 1990). Further, anomalies to EMH were also observed in the empirical research (Fama 1998). Fama's informationally efficient market model is criticized for its assumption that market participants arrive at a rational expectation forecast. It is argued that trade implies heterogeneity (bull and bear traders) and therefore returns can be predicted. Further, psychological and behavioral elements in stock price determination help predict future prices. In contrast to Fama's model, Campbell et al. (1997) states that asset returns are predictable to some degree. The consensus on this issue, thus, continues to be elusive. In this context, an attempt is made to empirically check whether stock returns in India, one of the emerging markets, follow random walk or not. The specific focus of the present chapter is to test linear dependence or lack of it in stock returns at the two premier exchanges in India namely, the National stock exchange (NSE) and Bombay stock exchange (BSE). The remainder of this chapter is structured as follows. In Sect. 2.2, a brief review of literature is offered. Section 2.3 describes the time series techniques carried out for the purpose. Sect 2.4 presents a discussion on empirical evidence and Sect. 2.5 concludes with a summary of the main findings.

2.2 Review of Previous Work

Literature on random walk characters of stock returns and EMH is truly abundant. Here an attempt is made to present a selective review of recent work.[1] Bachelier (1900) is perhaps the first who theorized the concept of market efficiency. In his work, he shows that the successive price changes are independent and identically distributed (*i.i.d*) because of randomness of information and possible unsystematic patterns in noise trading. In other words, the mathematical expectation of the speculation is zero. Osborne (1959) also provides a similar argument. The seminal works of Samuelson (1965) and Fama (1965, 1970) triggered much interest in this area.

Fama (1965) carries out empirical testing, shows the independence of price changes and concludes that the chartists exercise has no value. The studies of Working (1960), Niederhoffer and Osborne (1966) suggest that stock price movements are not serially correlated and, therefore, it is impossible to make abnormal profits from investment strategies. The independence of price changes remained unchallenged however. Jennergren and Korsvold (1974) in their study of 45 stocks on Norwegian and Swedish markets reject RWH and conclude that these markets may be 'weakly inefficient'. Solnik (1973) observes more apparent

[1] Fama (1970, 1998) present an excellent review of work on theory of efficient market and its genesis and history. The review of previous work carried out in the present study mainly focused on evidences from emerging markets.

deviations from random walk in European markets and cites inadequate disclosure norms, thin trading and insider trading as possible reasons for the inefficiency. French and Roll (1986) document a statistically significant negative serial correlation in daily returns but they are sceptical about the economic significance of such returns. In a similar vein, Keim and Stambaugh (1986) find statistically significant consistent predictability in stock prices by using forecasts of predetermined variables. Jagadeesh (1990) also reports predictability of stock returns. Frennberg and Hansson (1993) find serial dependence in stock returns of Sweden. However, Fama and French (1988) who documented negative autocorrelation in long horizon returns, suggest that such evidence does not necessarily imply inefficient market but may be the result of time-varying equilibrium expected returns generated by rational investors' behavior.

The early studies on market efficiency used serial correlation, runs, and spectral tests to check whether stock returns are characterized by random walk. The conventional techniques such as serial correlation seem to suffer from restrictive assumptions. They tend to be less efficient to capture the patterns in the returns. A new test, which is robust to heteroscedasticity, was proposed by Lo and MacKinlay (1988). In their study of weekly stock returns in the US, Lo and MacKinay (1988) reject the RWH for the weekly returns. They conclude that the mean reverting models of Poterba and Summers (1988), and Fama and French (1988) cannot give a satisfactory description of behavior of stock returns in the backdrop of strong evidence of positive correlation in the returns.

The most popular test carried out in the empirical testing of random walk since the publication of Lo and MacKinlay (1988) is the variance ratio test (henceforth, LMVR) proposed by them. Emerging and developing markets are expected to strongly reject random walk process of underlying returns because of underdevelopment of markets, thin trading and several frictions. However, similar to developed markets, studies from the emerging markets also have thrown inconsistent evidence. Butler and Malaikah (1992) empirically conclude that returns in Kuwait followed a random walk while rejecting RWH for Saudi Arabia. Abraham et al. (2002), who applied LMVR on emerging markets, observed dependence in index returns of Saudi Arabia, Kuwait, and Bahrain. However, the corrected returns support a weak form of market efficiency. The rejection of random walk in Middle Eastern markets has been identified to be the result of thin and infrequent trading (Butler and Malaikah 1992; Abraham et al. 2002).

The non-random walk behavior of stock returns is not just confined to the emerging Middle Eastern markets. Such behavior has been found in other emerging markets too. Urrutia (1995) finds positive autocorrelation in monthly returns of some Latin American countries. The studies by Ojah and Karemera (1999) and Greib and Reyes (1999) from Latin America empirically report mixed results. While the former finds evidence in support of random walk for Latin America, the latter finds significant autocorrelation in the Mexican market and random walk behavior in the Brazilian market.

The empirical results reported from Asian emerging markets are also mixed. Huang (1995), Alam et al. (1999), and Chaing et al. (2000) find that emerging

Asian markets, are not weak form efficient. In support of these findings, Husain (1997) concludes that RWH is not valid in Pakistan's equity markets because of strong dependence of stock returns. Thin trading, as in case of Middle Eastern markets, is one of the important sources of significant correlation in returns (Mustafa and Nishat 2007). Empirical findings on China, the leading emerging market, are quite inconsistent. Liu et al. (1997) upholds weak form efficiency for Chinese markets. Darant and Zhong (2000) and Lee et al. (2001) report independence of returns series for Chinese markets. Nevertheless, conflicting results in the same market were observed by Lima and Tabak (2004). While the Chinese-A[2] shares and Singapore stock market are weak form efficient, the Chinese-B shares and Hong Kong market revealed autocorrelation in the returns. The authors note that market capitalization and liquidity explain such conflicting results in the same market. The empirical findings of Lock (2007),Charles and Darne (2008) and, Fifield and Jetty (2008) support the earlier evidence on China that Share-A was weak form efficient while Share-B evidenced against it.

The LMVR tests individual variance ratios for a specific aggregation investment horizon and thus may result in size distortions. In order to overcome such deficiency in LMVR, later studies employed multiple variance ratio tests along with other tests. Ayadi and Pyun (1994) observed linear autocorrelation in Korean stock returns. Smith (2007) who investigated whether Middle East stock markets follow a random walk or not found that largely Israeli, Jordanian, Lebanese markets are weak form efficient while Kuwait and Oman markets reject the RWH. Smith et al. (2002) reports autocorrelation in return in Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria, and Zimbabwe. The study finds empirical evidence in support of random walk only in South Africa.

The empirical analysis for Australia for a longer period, 1875–2004, carried out by Worthington and Higgs (2009) rejected RWH and thus revealing strong serial dependence in the stock returns. Hoque et al. (2007) also observes autocorrelation in the majority of eight emerging markets researched. Using the multiple variance tests, an attempt was made by Benjelloun and Squalli (2008) to unmask sectoral efficiency in markets of Jordan, Qatar, Saudi Arabia, and United Arab Emirates. The study obtained inconsistent results among different sectors and different economies. The EMH in the European stock market was investigated by Borges (2011). The study employed tests namely, autocorrelation, runs, ADF unit root, and multiple variance ratio to test RWH. The study found that while the markets in France, Germany, the UK, and Spain followed a random walk, there was positive serial correlation in returns of Greece and Portugal. Nakamura and Small (2007) by using small-shuffle surrogate method found random walk characters in the US and Japanese stock returns.

[2] The ownership of Share A, denominated in local currency of China are restricted to domestic investors, while Share B denominated in US $ are exclusively for foreign investors. However, Chinese government from 2001 allowed domestic investors to trade Share B.

The early study on Indian stock market efficiency was perhaps carried out by Rao and Mukherjee (1971). Later, in a comparative study between BSE and NYSE, Sharma and Kennedy (1977) using runs test and spectral technique found that monthly returns on BSE were characterized by random walk. Similar evidence of random walk behavior was noted by Barua (1981), Gupta (1985).[3] Furthermore, Amanulla (1997), Amanulla and Kamaiah (1998), examined the behavior of stock returns on BSE Sensex, BSE National Index,[4] and 53 individual stocks. In addition to serial correlation and rank correlation tests, these two studies used the ARIMA (0, 1, 0) model to examine the distribution pattern of increments that received less focus on stock market efficiency studies in India. They concluded that the equity market in India was of weak form efficieny. However, Poshakwale (2002) found evidence against RWH. Thus, as in case of other markets, the results for India too remain inconclusive.

To sum up, although the literature on random walk and market efficiency is vast, there is no consensus among the researchers regarding efficiency of the market. The different tests implemented in the empirical investigation yielded different results. The empirical results of various studies appear to be sensitive to the tests employed for the analysis. However, conventional tests provide evidence in support of the RWH. Thin trading or non-synchronous trading, disclosure norms, various restrictions, and incomplete reforms are cited as important factors for the rejection of the random walk characterization of returns particularly in emerging markets. The review of literature shows mixed empirical evidence regarding the behavior of stock returns. In this context, the present chapter investigates the validity of the RWH in the Indian context by using the empirical tests described in the next section.

2.3 Weak Form Efficiency: Empirical Tests

This section presents description of time series techniques used to test the RWH.

2.3.1 Parametric Tests

2.3.1.1 Autocorrelation Test

Autocorrelation estimates may be used to test the hypothesis that the process generating the observed return is a series of *i.i.d* random variables. It helps to

[3] Amanulla and Kamaiah (1996) presented an excellent and comprehensive review of early Indian evidence on market efficiency. Also see, Barua et al. (1994). Repetition is avoided here.

[4] This is now known as BSE 100 Index traded on BSE.

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

$$\mathrm{LB} = n(n+2)\sum\nolimits_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \tag{2.1}$$

where n is number of observation, m lag length. The test follows Chi square (χ^2) distribution.

2.3.1.2 Lo and MacKinlay (1988) Variance Ratio Test

Lo and MacKinaly (1988) proposed the variance ratio test, which is capable of distinguishing between several interesting alternative stochastic processes[5] For example, if the stock prices are generated by a random walk process, then the variance of monthly sampled log-price relatives must be four times as large as the variance of weekly return.

Let a stochastic process represented by

$$r_t = \mu + \ln P_t - P_{t-1} + \varepsilon_t \tag{2.2}$$

where r_t is stock returns, μ is drift parameter, $\ln P_t$ and P_{t-1} is log price at t time and P_{t-1} is price at t – 1. Under random walk, increments of ε_t are *i.i.d.* and disturbances are uncorrelated. 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, $r_t(2) \equiv r_t - r_{t-1}$, to twice the variance of a one-period return r_t. Then variance ratio VR(2) is

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

$$= \frac{2\,\mathrm{Var}[r_t] + 2\,\mathrm{Cov}[r_t, r_t - 1]}{2\,\mathrm{var}[r_t]}$$

$$\mathrm{VR}(2) = 1 + \rho(1) \tag{2.3}$$

where $\rho(1)$ is the first order autocorrelation coefficient of returns $\{r_t\}$. 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 MacKinaly (1988) showed that q period variance ratio satisfies the following relation:

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[5] A detailed discussion on the test and its empirical application can be seen in Campbell et al .(1997).

$$\mathrm{VR}(q) = \frac{\mathrm{Var}[r_t(q)]}{q.\mathrm{Var}[r_t]} = 1 + 2\sum\nolimits_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\rho^k \tag{2.4}$$

where $r_t(k) \equiv r_t + r_{t-1} + \ldots + r_{t-k+1}$ and $\rho(k)$ is the kth order autocorrelation coefficient of $\{r_t\}$. Equation (2.4) shows that at all q, $\mathrm{VR}(q) = 1$. For all definition of random walk[6] (as defined in Chap. 1) to hold, variance ratio is expected to be equal to unity (Campbell et al. 1997). The test is based on standard asymptotic approximations. Lo-MacKinlay proposed $Z(q)$ standard normal test statistic[7] under the null hypothesis of homoscedastic increments and $\mathrm{VR}(q) = 1$, test statistic $Z(q)$ is given by

$$Z(q) = \frac{\mathrm{VR}(q) - 1}{\Phi(q)^{1/2}} \tag{2.5}$$

which is asymptotically distributed as N (0,1).

In the Eq. (2.5), asymptotic variance $\Phi(q)$ is defined as

$$\Phi(q) = \left(\frac{2(2q-1)(q-1}{3q}\right)^2 \tag{2.6}$$

To ensure rejection of RWH that is not because of heteroscedasticity, a common feature of financial returns, Lo-MacKinlay constructed a heteroscedastic robust test statistic, $Z^*(q)$

$$Z^*(q) = \frac{\mathrm{VR}(q) - 1}{\Phi^*(q)^{1\backslash 2}} \tag{2.7}$$

which follows standard normal distribution asymptotically. The asymptotic variance $\Phi^*(q)$ is

$$\Phi^*(q) = \sum\nolimits_{j=1}^{q-1}\left(\frac{2(2q-1)}{q}\right)^2 \delta(j) \tag{2.8}$$

where

$$\delta(j) = \frac{\sum_{t=j+1}^{nq}(r_t - \widehat{\mu})^2(r_{t-j} - \widehat{\mu})^2}{\left[\sum_{t=1}^{nq}(r_t - \widehat{\mu})^2\right]^2} \tag{2.9}$$

Thus, according to variance ratio test, the returns process is a random walk when variance ratio at a holding period q is expected to be unity. If it is less than

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[6] These definitions are independence and identical distributions, independent increments, and uncorrelated elements. Also see Campbell et al. (1997).

[7] A detailed discussion on sampling distribution, size and power of the test can also be found in Lo and MacKinlay (1999).

unity, it implies negative autocorrelation and if it is great than one, indicates positive autocorrelation.

2.3.1.3 Chow and Denning (1993) Multiple Variance Ratio Test

The variance ratios 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 random walk is rejected if it is rejected for some q value. Therefore, it is essentially an individual hypothesis test. The variance ratio of Lo and MacKinlay (1988) tests whether 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 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 null $\mathrm{VR}(q) = 1$, but in multiple variance ratio test, $M_r = (q_i) = \mathrm{VR}(q) - -1 = 0$. This can be generalized to a set of m variance ratio tests as

$$\{M_r(q_i)|i = 1, 2..., m\} \tag{2.10}$$

Under RWH, multiple and alternative hypotheses are as follows

$$H_{0i} = M_r = 0 \text{ for } i = 1, 2, \ldots, m \tag{2.11a}$$

$$H_{1i} = M_r(q_i) \neq 0 \text{ for any } i = 1, 2, \ldots, m \tag{2.11b}$$

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

$$\mathrm{CD}_1 = \sqrt{T}\max|_{1 \leq i \leq} Z(q_i)| \tag{2.12}$$

In Eq. (2.12), $Z(q_i)$ is defined as in Eq. (2.5). Chow-Denning test follows studentized maximum modulus, $\mathrm{SMM}(\alpha, m, T)$, distribution with m parameters and T degrees of freedom. Similarly, heteroscedastic robust statistic of Chow-Denning is given as

$$\mathrm{CD}_2 = \sqrt{T}\max|_{1 \leq i \leq} Z^*(q_i)| \tag{2.13}$$

where $Z^*(q_i)$ is defined as in Eq. (2.7). The RWH is rejected if values of standardized test statistic, CD_1 or CD_2 is greater than the SMM critical values at chosen significance level.

2.3.2 Non-parametric Tests

2.3.2.1 Runs Test

Runs test is one of the important non-parametric tests of 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 the data is generated by a random process. If the actual runs are close to expected number of runs, it indicates that the returns are generated by random process. The expected number of runs, ER, is computed as

$$\mathrm{ER} = \frac{X(X-1) - \sum_{i=1}^{3} c_i^2}{X} \tag{2.14}$$

where X is total number of runs, c_i is number of returns changes of each category of sign ($i = 1, 2, 3$). The ER in Eq. (2.14) has an approximate normal distribution for large X. Hence, to test null hypothesis, standard Z-statistic can be used.[8]

2.3.2.2 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). The test can be used for testing against a variety of possible deviations from independence including linear dependence, nonlinear dependence, or chaos. The BDS test uses correlation dimension of Grassberger and Procaccia (1983). To perform the test[9] for a sample of n observations $\{x_1, \ldots\ldots, x_n\}$, an embedding dimension m, and a distance ε, the correlation integral $C_m\,(n, \varepsilon)$ is estimated by

$$I\,(x_s, x_t, \varepsilon) = \begin{cases} 1 & \text{if} |x_s - x_t| < \varepsilon, \\ 0 & \text{otherwise,} \end{cases}$$

$$I_m\,(x_s, x_t, \varepsilon) = \prod_{k=0}^{m-1} I(x_{s+k}, x_{t+k}, \varepsilon),$$

$$C_m(n, \varepsilon) = \frac{2}{(n-m)(n-m+1)} \sum_{s=1}^{n-m} \sum_{t=S+1}^{n-m+1} I_m(x_s, x_t, \varepsilon)\cdot \tag{2.15}$$

The function $I\,(\cdot)$ indicates whether the observations at times s and t are near each other or not, as determined by the distance ε. The product $I_m\,(\cdot)$ is only one when the two m-period histories (x_s, $x_{s\,+\,1}$, ……, $x_{s\,+\,m\,-\,1}$) and (x_t, $x_{t\,+\,1}$, ……., $x_{t\,+\,m\,-\,1}$) are near each other in the sense that each term $x_{s\,+\,k}$ is near $x_{t\,+\,k}$. The estimate of the correlation integral is the proportion of pairs of m-period

8 For further discussion on runs test, see Siegel (1956).

9 The BDS test discussion is based on Taylor (2005).

histories that are near each other. For observations from many processes, limit is defined as

$$\lim_{n \to \infty} C_m(n, \varepsilon)$$

When the observations are from an *i.i.d* processes, the probability of m consecutive near pairs of observations is simply the product of m equal probabilities and hence

$$C_m(\varepsilon) = C_1(\varepsilon)^m$$

When the observations are from a chaotic process, the conditional probability of x_{s+k} being near x_{t+k}, given that x_{s+j} is near x_{t+j} for $0 \leq j < k$, is higher than the conditional probability and hence

$$C_m(\varepsilon) > C_1(\varepsilon)^m$$

The BDS considers the random variable $\sqrt{n}(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m$ which, for an i.i.d process, converges to a normal distribution as n increases. The test statistic is given below.

$$W_m(\varepsilon) = \sqrt{\frac{n}{\hat{V}_m}}(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m) \tag{2.16}$$

where the consistent estimator of V_m namely, $\hat{V}_m$ is given by

$$\hat{V}_m = 4(k^m + (m-1)^2 C^{2m} - m^2 k C^{2m-2} + 2\sum_{j=1}^{m-1} k^{m-j} C^{2j} \tag{2.17}$$

with $C = C_1\ (n, \varepsilon)$ and

$$K = \frac{6}{(n-m-1)(n-m)(n-m+1)} \sum_{S=2}^{n-m} \left(\left[\sum_{r=1}^{s-1} I_m(x_r, x_s) \right] \left[\sum_{t=S+1}^{n-m+1} I_m(x_s, x_t) \right] \right) \tag{2.18}$$

It has power against a variety of possible alternative speciations like nonlinear dependence and chaos. The BDS statistics is commonly estimated at different m, and ε.

2.4 Discussion on Empirical Results

This section discusses the empirical results of parametric and non-parametric tests that are carried out in this study. The descriptive statistics for the 14 indices are given in Table 2.1. The highest average returns are obtained in CNX 100. The CNX Infrastructure and CNX Bank Nifty are the other indices, which show higher mean returns. This reflects the performance of these indices owing to the considerable growth of infrastructure and banking sector in India because of the

Table 2.1 Descriptive statistics

Index	Mean	Min	Max	Standard deviation	Skeweness	Kurtosis	J-B test statistics	*P* value of JB test
S & P CNX Nifty	0.000352	−0.130538	0.079690	0.017485	−0.512508	4.366738	2479.67	0.000
CNX Nifty Junior	0.000458	−0.131333	0.082922	0.020528	−0.668462	3.746319	1950.09	0.000
S & P CNX Defty	0.000234	−0.141130	0.089858	0.018532	−0.472054	4.548736	2659.12	0.000
CNX 100	0.000667	−0.130493	0.080065	0.018059	−0.835206	5.683283	2282.31	0.000
CNX 500	0.000436	−1.288471	0.076944	0.017744	−0.761208	4.460254	2272.06	0.000
BSE Sensex	0.000345	−0.118091	0.079310	0.017810	−0.399402	3.339056	1377.15	0.000
BSE 100	0.000400	−0.599342	0.552933	0.023934	−1.459145	241.725	6827.37	0.000
BSE 200	0.000412	−2.299381	2.297634	0.063972	−0.068990	1188.688	1650.41	0.000
BSE 500	0.000273	−0.249827	0.075327	0.018659	−1.690044	17.02682	2901.32	0.000
BSE Midcap	0.000144	−0.120764	0.104317	0.018377	−1.266593	7.827763	3689.15	0.000
BSE Smallcap	0.000171	−0.108357	0.132050	0.019092	−0.874436	5.399936	1755.87	0.000
CNX IT	0.000187	−2.365839	0.145567	0.051938	−32.15014	1462.399	2631.86	0.000
CNX Bank Nifty	0.000614	−0.151380	0.114014	0.021785	−0.423283	4.036178	1638.38	0.000
CNX Infrastructure	0.000659	−0.150214	0.102127	0.021826	−0.758949	5.930724	2042.52	0.000

Note Basic statistics for 14 indices are given in the table. The null of skewness and kurtosis = 0, is significantly rejected for all the chosen index

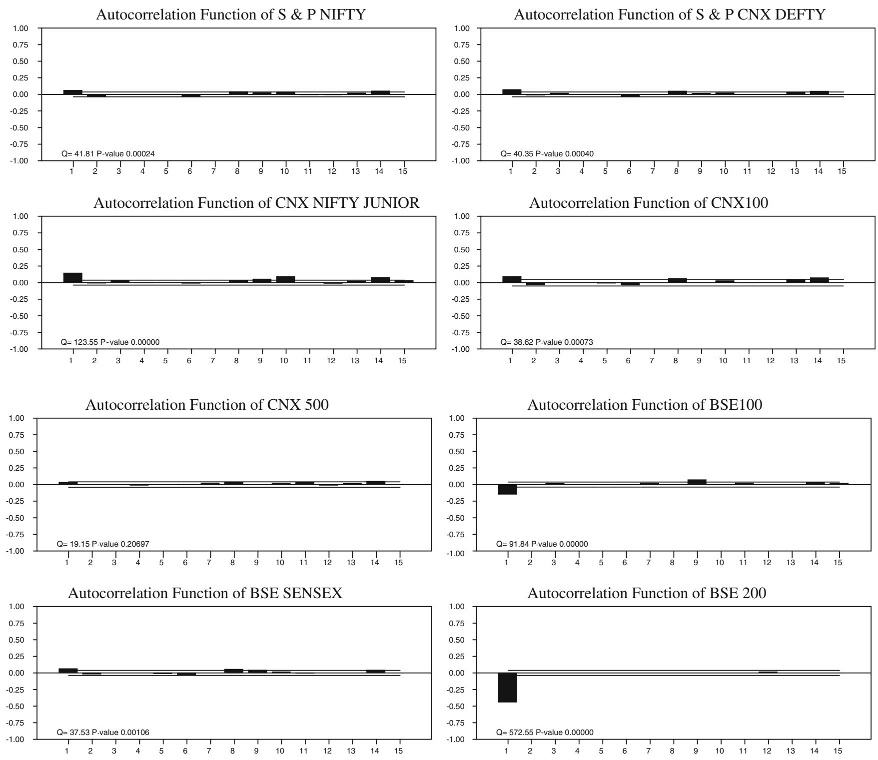

Fig. 2.1 Autocorrelation function of index returns

significant increase in the government outlay along with encouraging participation of private players. Further, the BSE 200 has the highest standard deviation (0.0639) which represents higher volatility and lowest is of CNX Nifty (0.0174) and the CNX 500 (0.0177). The CNX IT registered the higher volatility among the selected sectoral indices due to fluctuation in the international market. The returns of the selected index series are negatively skewed implying that the returns are flatter to the left compared to the normal distribution. The significant kurtosis indicates that return distribution has sharp peaks compared to a normal distribution. Further, the significant Jarque and Bera (1980) statistic confirmed that index returns are non-normally distributed. This confirms the stylized facts of stock returns. This study employs Ljung-Box test to check whether all autocorrelations are simultaneously equal to zero. The plots of autocorrelation function of indices are given in Fig. 2.1which clearly display that autocorrelations even up to 15 lags are significant.

Ljung-Box test statistics are provided in Table 2.2. It is evident from test statistics that the null hypothesis of no serial correlation cannot be rejected at any conventional significance level for CNX IT and CNX 500 index returns and thus indicate random walk behavior. The rest of indices show strong autocorrelation in

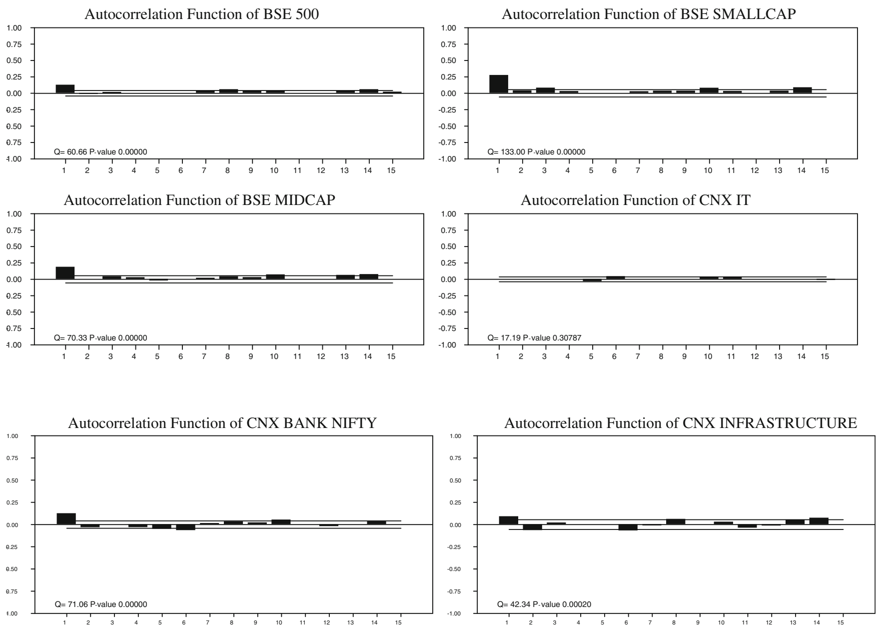

Fig. 2.1 continued

Table 2.2 Autocorrelations of index returns

Index returns	Lags	LB Q statistic	Q significance
S & P CNX Nifty	15	41.81	0.0002*
CNX Nifty Junior	15	123.55	0.0000*
S & P CNX Defty	15	40.35	0.0004*
CNX 100	15	38.62	0.0007*
CNX 500	15	19.15	0.2070
BSE Sensex	15	37.53	0.0011*
BSE 100	15	91.84	0.0000*
BSE 200	15	572.55	0.0000*
BSE 500	15	60.66	0.0000*
BSE Midcap	15	70.33	0.0000*
BSE Smallcap	15	133.00	0.0000*
CNX IT	15	17.19	0.3079
CNX Bank Nifty	15	71.06	0.0000*
CNX Infrastructure	15	42.34	0.0002*

Note The Ljung-Box (LB) Q statistic is given in the table up to 15th order autocorrelation for all series. Asterisked value rejects the null hypothesis at 1 % level of significance. The critical values of the test statistics reject null hypothesis of no serial correlation at all conventional significance level except for CNX IT Junior and CNX 500 the returns series as the null is rejected at the 1 % significance level (see Table 2.2).

Furthermore, Lo and MacKinlay (1988) test is carried out and variance ratios and corresponding homoscedastic increments and heteroscedasticity robust tests statistic for each index returns at various investment horizons like 2, 4, 8, and 16 are presented in second and third rows, respectively, in Table 2.3. The test results presented in table show that with the sole exception of BSE 100, variance ratios for all other indices at all investment horizons are greater than unity. The significant homoscedastic and heteroscedastic statistics reject RWH for the index returns namely, Nifty Junior, BSE 500, BSE Midcap, and BSE Smallcap including CNX 500 (with exception at lag 2 and 4) at all investment horizons or holding periods. The variance ratios for these indices are greater than unity and thus indicate the presence of significant positive autocorrelations in the returns. However, the test statistic for CNX IT and the BSE 200, BSE Sensex supports the presence of random walk, as value of test statistic is lower than the critical value.

The volatility changes over time 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. The homoscedastic statistic given in second row in Table 2.3 for CNX Nifty, CNX Infrastructure at lag 2, CNX Defty, and CNX 100 at lag 2 and 4 and for BSE 100 at all the investment horizons rejects RWH. However, heteroscedastic robust statistic is insignificant for these indices at all lags (investment horizons). This shows that rejection of random walk for these indices is because of conditional heteroscedasticity. Otherwise, the results conform to RWH for these index returns and hence rejection of null of random walk is not meaningful. In short, the LMVR results suggest autocorrelation only in Nifty Junior, CNX 500, BSE500, BSE Midcap, BSE Smallcap and sectoral index, CNX Bank Nifty returns.

The mixed results from the LMVR test reveals the fact that the individual variance ratio test of LMVR do not give consistent evidence at different holding periods, since the null of random walk requires variance ratios for all holding periods to be equal to one. In this context, the Chow and Denning (1993) multiple variance ratio test assumes relevance. The maximum homoscedastic and heteroscedastic robust test statistics are reported in Table 2.4. The maximum homoscedastic values of BSE Sensex and CNX 500 are less than critical value (2.49) and hence cannot reject the null of random walk. The statistics for other index returns reject the null of random walk at 5 % level of significance. However, the homoscedastic statistics are less relevant for meaningful inferences because of rejection may be due to heteroscedasticity. The heteroscedastic robust Chow-Denning test statistics significantly reject the null of random walk for the CNX Nifty Junior, CNX 500, BSE 500, BSE Midcap and BSE Smallcap, and the CNX Bank Nifty returns suggesting serial dependence (see Table 2.4). It is to be noted that LMVR (both homoscedastic and heteroscedastic) test also rejects null of RWH for these indices. On the other hand, return indices such as CNX Nifty, CNX Defty, CNX100, BSE Sensex, BSE 100, BSE 200 and sectoral index CNX IT, and CNX Infrastructure validate RWH since Chow-Denning statistic values are less

Table 2.3 Variance ratio tests statistic for index returns

Index returns	Lo-MacKinlay variance ratios for different investment horizons			
	2	4	8	16
S & P CNX Nifty	1.062	1.053	1.036	1.087
	(3.35)*	(1.53)	(0.65)	(1.07)
	(1.93)	(0.92)	(0.41)	(0.72)
CNX Nifty Junior	1.143	1.209	1.231	1.072
	(7.75)*	(6.04)*	(4.22)*	(4.96)*
	(4.26)*	(3.46)*	(2.59)*	(3.29)*
S & P CNX Defty	1.072	1.094	1.091	1.163
	(3.89)*	(2.72)*	(1.66)	(2.00)*
	(2.22)*	(1.62)	(1.04)	(1.32)
CNX 100	1.093	1.096	1.054	1.126
	(3.65)*	(2.01)*	(0.71)	(1.12)
	(1.85)	(1.06)	(0.40)	(0.68)
CNX 500	1.138	1.189	1.221	1.380
	(6.81)*	(4.98)*	(3.68)*	(4.25)*
	(3.63)*	(2.78)*	(2.21)*	(2.75)*
BSE Sensex	1.070	1.069	1.034	1.093
	(3.66)*	(1.94)	(0.61)	(1.10)
	(2.34)*	(1.26)	(0.40)	(0.76)
BSE 100	0.840	0.769	0.719	0.770
	(−8.37)*	(−6.46)*	(−4.98)*	(−2.74)*
	(−0.75)	(−0.72)	(−0.75)	(−0.56)
BSE 200	1.011	1.014	1.023	1.058
	(0.61)	(0.40)	(0.42)	(0.69)
	(0.81)	(0.54)	(0.57)	(0.95)
BSE 500	1.123	1.173	1.217	1.396
	(5.91)*	(4.42)*	(3.50)*	(4.29)*
	(3.39)*	(2.66)*	(2.24)*	(2.96)*
BSE Midcap	1.220	1.350	1.464	1.688
	(7.85)*	(7.85)*	(5.59)*	(5.57)*
	(3.43)*	(3.10)*	(2.90)*	(3.29)*
BSE Smallcap	1.279	1.504	1.733	2.069
	(9.96)*	(9.60)*	(8.84)*	(8.65)*
	(5.28)*	(5.42)*	(5.45)*	(5.86)*
CNX IT	1.008	1.016	1.026	1.113
	(0.43)	(0.47)	(0.48)	(1.39)
	(0.33)	(0.43)	(0.44)	(1.20)
CNX Bank Nifty	1.123	1.146	1.049	1.047
	(5.90)*	(3.73)*	(0.80)	(0.51)
	(3.21)*	(2.16)*	(0.50)	(0.34)
CNX Infrastructure	1.091	1.078	1.031	1.061
	(3.26)*	(1.49)	(0.38)	(0.49)
	(1.63)	(0.78)	(0.21)	(0.30)

Note Table report Lo-MacKinalay test results. The variance ratios VR (q) are reported in the main rows and variance test statistic $Z(q)$ for homoscedastic increments and, for heteroscedastic—robust test statistics $z^*(q)$ are given in the second and third row parentheses respectively. Under the null of random walk, the variance ratio value is expected to be equal to one. Asterisked values indicate rejection of the null of random walk hypothesis at 5 % level significance

Table 2.4 Multiple variance ratio test statistics for index returns

Index returns	Homoscedastic statistic	Heteroscedastic statistic
S & P CNX Nifty	3.31803*	1.93554
CNX Nifty Junior	7.74220*	4.26921*
S & P CNX Defty	3.88990*	2.22679
CNX 100	3.60146*	1.85454
CNX 500	1.69682	3.62379*
BSE Sensex	3.30603	2.34265
BSE 100	8.32605*	0.76055
BSE 200	8.84280*	0.82037
BSE 500	5.98647*	3.37238
BSE Midcap	6.73254*	3.42666*
BSE Smallcap	9.93798*	5.27285*
CNX IT	1.38788*	0.53818
CNX Bank Nifty	5.80567*	3.23927*
CNX Infrastructure	3.22557*	1.60863

Note The multiple variance ratio homoscedastic (CD_1) and heteroscedastic (CD_2) statistic of Chow-Denning test are reported here. The critical value is 2.49. Asterisked values indicate rejection of null of random walk hypothesis at 5 % level of significance

than the critical values for these index returns. Furthermore, Chow-Denning results are not significantly different from those of LMVR. However, diverse results and statistical size distortion problem can be mitigated by Chow-Denning test and therefore results of this test are preferable. It may be noted that the parametric tests provided diverse results where five out of eight indices traded on NSE and three out of six indices traded on BSE validate RWH while rest of the indices reject the RWH. This indicates intra-market and intra-exchange variations in the behavior of stock returns.

This study also employed two non-parametric tests namely the runs test and the, BDS test which are robust to distribution of the returns. The choice of these tests is appropriate especially in the light of the observation made in the present study that returns series are non-normally distributed (see Table 2.1). The runs test is a popular non-parametric test of RWH. Table 2.5 provides runs test results.

Actual runs (see, second column of Table 2.1) are number of change in returns, positive or negative, observed in the returns series. The expected runs given in third column are the change in returns required, if the data is generated by random process. If the actual runs are close to expected number of runs, it indicates that the returns are generated by random process. It can be seen from the table that the actual runs of index returns namely CNX Nifty, CNX Nifty Junior, CNX Defty, BSE Sensex, BSE 100, BSE 200, CNX 500, CNX Bank Nifty, and BSE 500 are less than the expected runs. The significant negative *Z* values indicate the positive correlation in these returns series. The number of runs for CNX IT, CNX Infrastructure, BSE Midcap and BSE Smallcap returns exceeds the expected

Table 2.5 Runs test statistics for index returns

Index returns	Actual runs	Expected runs	Z-statistic
S & P CNX Nifty	1,144	1,258	−4.59*
CNX Nifty Junior	1,081	1,183	−4.35*
S & P CNX Defty	1,193	1,253	−2.42*
CNX 100	533	546	−0.85
CNX 500	872	993	−5.5*
BSE Sensex	1,126	1,231	−4.29*
BSE 100	1,104	1,231	−6.41*
BSE 200	1,079	1,228	−6.10*
BSE 500	851	982	−5.10*
BSE Midcap	557	472	4.36*
BSE Smallcap	471	219	5.28*
CNX IT	1,183	939	11.32*
CNX Bank Nifty	1,114	1,259	−5.83*
CNX Infrastructure	670	423	17.31*

Note Under null of random walk, actual runs should be equal to expected runs. Asterisked values indicate rejection of null of random walk at 1 % level of significance

number of runs. For these indices, the positive sign of the significant Z value suggest a negative correlation. With the sole exception of CNX 100, the hypothesis of random walk has been rejected for all the indices. In other words, behaviour of Indian stock returns is not explained by the random walk theory.

The BDS test is performed at various embedded dimensions (m) like 2, 4, 6, 8, and 10 and also at various distances like 0.5, 0.75, 1, 1.25, and 1.5 s where s denotes the standard deviation of the return. The BDS test statistic followed by p-values in parentheses is furnished in Table 2.6. In the BDS test, the null hypothesis is that return series are *i.i.d* and rejection of the null implies that RWH does not pass the test. It is very clear from the results that BDS test rejects the null hypothesis of independence and thereby RWH too for all the 14 indices. It shows that stock returns are linearly dependent. The dependence may be linear or non-linear in the returns series which is not specified here.[10] The BDS test has been known to be having better statistical power properties than the runs test. Besides, the latter test suffers from a reduction in test power due to loss of information in the transformation from returns to their signs. Overall, the results of the runs and BDS test rejected the null of *i.i.d* (the stricter definition of random walk) at the conventional significant levels.

This empirical analysis shows that behavior of stock index returns in India both on the NSE and BSE, largely, do not support RWH. The parametric multiple variance ratio test results support the view that stocks returns follow random walk for indices namely, S& P CNX Nifty, S &P CNX Defty, CNX 100, BSE Sensex, BSE 100 and sectoral CNX IT, and CNX Infrastructure. The LMVR test results for

[10] The issue of alternative specifications like non-linear dependence are detailed in Chap. 4.

Table 2.6 BDS test statistics for index returns

Index returns	$m = 2$, $\varepsilon = 0.5S$	$m = 4$, $\varepsilon = 0.75S$	$m = 6$, $\varepsilon = S$	$m = 8$, $\varepsilon = 1.25S$	$m = 10$, $\varepsilon = 1.5S$
S & P CNX Nifty	12.38 (0.0000)	20.45 (0.0000)	26.80 (0.0000)	31.25 (0.0000)	32.25 (0.000)
CNX Nifty Junior	16.00 (0.0000)	24.28 (0.0000)	30.74 (0.0000)	35.60 (0.0000)	36.99 (0.0000)
S & P CNX Defty	12.69 (0.0000)	20.31 (0.0000)	26.23 (0.0000)	30.56 (0.0000)	31.77 (0.0000)
CNX 100	11.48 (0.0000)	18.82 (0.0000)	25.53 (0.0000)	29.40 (0.0000)	29.72 (0.0000)
CNX 500	14.77 (0.0000)	23.20 (0.0000)	31.01 (0.0000)	35.92 (0.0000)	36.36 (0.0000)
BSE Sensex	12.83 (0.0000)	21.42 (0.0000)	28.39 (0.0000)	33.38 (0.0000)	34.70 (0.0000)
BSE 100	15.55 (0.0000)	24.20 (0.0000)	29.30 (0.0000)	30.35 (0.0000)	28.83 (0.0000)
BSE 200	16.07 (0.0000)	23.03 (0.0000)	24.58 (0.0000)	23.51 (0.0000)	21.48 (0.0000)
BSE 500	14.58 (0.0000)	23.35 (0.0000)	30.64 (0.0000)	34.37 (0.0000)	34.05(0.0000)
BSE Midcap	13.39 (0.0000)	18.92 (0.0000)	23.91 (0.0000)	25.53 (0.0000)	24.32 (0.0000)
BSE Smallcap	13.91 (0.0000)	17.90 (0.0000)	21.53 (0.0000)	23.32 (0.0000)	22.87 (0.0000)
CNX IT	19.35 (0.0000)	25.36 (0.0000)	25.64 (0.0000)	25.07 (0.0000)	24.16 (0.0000)
CNX Bank Nifty	12.18 (0.0000)	17.86 (0.0000)	21.90 (0.0000)	24.63 (0.0000)	25.71 (0.0000)
CNX Infrastructure	10.37 (0.0000)	17.67 (0.0000)	23.69 (0.0000)	26.67 (0.0000)	26.89 (0.0000)

Note The table reports the BDS test results. Here, 'm' and 'ε' denote the dimension and distance, respectively and 'ε' equal to various multiples (0.5, 0.75, 1, 1.25 and 1.5) of standard deviation (s) of the data. The value in the each cell is the BDS test statistic followed by the corresponding p value in parentheses. The asymptotic null distribution of test statistics is N (0.1). The BDS statistic tests the null hypothesis that the increments are independent and identically distributed, where the alternative hypothesis assumes a variety of possible deviations from independence including nonlinear dependence and chaos. All the BDS values are statistically significant at 1 % level these indices are found significant only for short horizons like 2–4 days and following random walk afterwards (longer horizons). The possible explanation for the this behaviour of stock returns is that the information in short-horizon is not instantly reflected in returns and thus provide opportunity for excess returns to those who have access to this information. Later, as the time horizon increases, information is reflected in stock returns leading to improvement in informational efficiency. The parametric results for other indices show strong autocorrelation. The non-parametric tests, which are robust to non-normality, reject random walk characteristics in Indian stock returns on NSE and BSE. The view that the likelihood of rejection of RWH in case of larger indices having higher market capitalization and higher liquidity is less than their lower counterparts is supported in case of BSE, as rejection of null is stronger in case of BSE Midcap and BSE Smallcap. However, this is not fully observed in indices traded on NSE.

2.5 Concluding Remarks

This chapter has investigated the behavior of stock returns by testing RWH, in emerging Indian equity market. The specific objective of the chapter was to test weak form of market efficiency in Indian equity market. Toward this end, parametric and non-parametric tests are used to analyze the daily data on 14 market indices from two major stock exchanges namely, the NSE and BSE. The results from parametric tests offered mixed results and suggest random walk characteristics in returns of highly liquid and considerable market capitalized indices on BSE. However, this has not found empirical support from evidence on NSE indices. The sector-wise results largely indicate random walk behavior for the selected indices. The empirical results from the non-parametric runs and BDS tests resoundingly reject the RWH in Indian stock markets. However, it is to be noted that these two tests examine the stricter definition of random walk. In the light of the present evidence, it is necessary that the regulatory authority and policy making body ensure dissemination of information so that price can reflect the information quickly.

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