Market Efficiency, Long Memory and Volatility in Indian Equity Market

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I hereby declare that the work presented in the thesis entitled "Market ***Efficiency, Long Memory and Volatility in Indian Equity Market"*** has been carried out by me under the supervision of Professor Bandi Kamaiah, Department of Economics, University of Hyderabad, and to the best of my knowledge no part of this thesis was earlier submitted for the award of any research degree or diploma of any University or Institution.

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This is to certify that, the research embodied in the present thesis entitled "Market ***Efficiency, Long Memory and Volatility in Indian Equity Market"*** has been carried out by Mr. Gourishankar S. Hiremath under my supervision for the full period prescribed under PhD ordinances of the University and no part of this thesis was earlier submitted for the award of any research degree of any University.

Professor Bandi Kamaiah

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Abbreviations

ACF	Autocorrelation function
AGBR	Andrews and Guggenberger bias reduced test
AR	Autoregressive
ARCH	Autoregressive conditional heteroscedasticity
ARFIMA	Autoregressive fractionally integrated moving average
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
ASEAN	Association of South East Asian Nations
BDS	Broack, Dechert, Sheinkman, LeBaron (1996)
BSE	Bombay Stock Exchange
CMIE	Centre for Monitoring Indian Economy
CRR	Cash reserve ratio
DFA	Detrended fluctuation analysis
ECBs	External commercial borrowings
EMH	Efficient market hypothesis
FDI	Foreign direct investment
FEMA	Foreign Exchange Management Act
FIGARCH	Fractionally integrated generalized autoregressive conditional heteroskedasticity
FII	Foreign institutional investors
GARCH	Generalized autoregressive conditional heteroskedasticity
GPH	Geweke Porter-Hudak semiparametric test
IGARCH	Integrated generalized autoregressive conditional heteroskedasticity
IRA	Insurance Regulatory Authority
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LOMAC	Lo and MacKinlay variance ratio test
MENA	Middle East and North Africa
MLE	Maximum likelihood estimation
NSE	National Stock Exchange

Abbreviations

NYSE	New York Stock Exchange
QMLE	Quasi maximum likelihood estimator
R/S	Rescaled range statistics
RBI	Reserve Bank of India
RGSE	Robinson‟s Gaussian semiparametric estimation
RWH	Random walk hypothesis
RMW	Random Walk Model
SEBI	Securities and Exchange Board of India
SSS	Small-shuffle surrogate
UTI	Unit Trust of India
WRSVR	Wright‟s ranks and sighs variance ratio test

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INRODUCTORY BACKGROUND, ISSUES AND OBJECTIVES

1.0 Introduction

Market efficiency has been a focal point of research in finance literature. An efficient equity market plays a vital role in the economy. In the absence of an efficient market, allocation of capital would not be according to the demand of the economy and consequently economic growth would be retarded. A market is said to be efficient if it is informationally efficient. In an informationally efficient market current prices reflect all the available and relevant information (Fama, 1970). Such markets do not provide consistent abnormal returns. This is known as the Efficient Market Hypothesis (EMH), which is quite prominent in neoclassical finance literature. The early empirical evidence on EMH demonstrated that stock returns follow a random walk process. The implication of the random walk process is that it is not possible to predict future returns based on past information of stock returns. In short, it is not possible to 'beat the market'.

1.1. Schools of Thought on Behaviour of Stock Returns

There are two more schools of thought which describe stock returns behaviour namely, Fundamental school and Technical school.

1.1.1 The Fundamental School

The Fundamental school believes that the fundamental factors determine behaviour of stock returns. The fundamentalists seek to analyze stock prices on the basis of earning and dividend prospects of the firm which they believe as key-decision variables. They also analyze quality of firm's management, status of industry, business cycles, financial statements of firms, etc[1].

1.1.2 The Technical School

Technical school or analysis asserts that information possessed in stock prices is of great use to predict future returns. Technical analysts, popularly known as chartists use a variety of approaches such as Dow theory, filter rules, trading range breaks, Elliot wave theory, Kondratieff's wave principle, moving averages, relative strength etc. The basic contention of technical analysis is that forces of demand and supply reflect the pattern of trade volume and prices and these patterns get repeated. By a careful analysis of past sequences of prices, future prices could be predicted, thus making it possible to 'beat the market'.[2] Behavioural finance, one of the emerging areas asserts that investors are irrational and market sentiments such as fear and greed explain behaivour of returns.

The past three and half decades have produced a large volume of research on stock market efficiency. The quest for stock market efficiency in India began with the early work of Krishna Rao and Mukherjee (1971). The studies of Amanulla and Kamaiah (1998), Poshakwale (2002) and Chaudhuri and Wu (2004), are important additions to the recent literature. A quick review of the previous work reveals that consensus on this issue has been elusive. Nevertheless, the ongoing scientific debate, as Lo and MacKinaly (1999) observe, has provided new insights into the economic structure of financial markets.

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[1] For a detailed theoretical discussion on fundamental analysis, see Molodovsky *et al* (1965).
[2] A detailed description of technical analysis can be seen in Levy (1966), Jensen and Bennington (1970).

1.2 Theoretical Foundations of EMH

Efficient market theory originated during the beginning of twentieth century. The seminal work of Bachelier (1900) laid theoretical foundation for the theory of market efficiency. Bachelier (1900) in his investigation of French Government Bonds concluded that prices fluctuate randomly as they are independent and identically distributed (i.i.d). Bachelier (1900) observed that 'past, present and even discounted future events are reflected in market prices, but often show no apparent relation'. In other words, past movement of prices would not guide future movement of prices.[3] Further, Kendell (1953) found no predictable components in stock prices and therefore stock prices appeared to evolve randomly.

The pioneering work of Samuelson (1965) in fact added rigour to the theory of market efficiency. 'In competitive market, there is a buyer for every seller. If one could be sure that a price would rise, it would have risen' (Samuelson, 1965). Utilizing a framework of general stochastic model of price, he deduced his theorem in which future changes in prices are uncorrelated with past changes in prices. In other words, as the current prices properly anticipate information, prices fluctuate randomly in response to new information.

In a survey of efficient capital markets, Fama (1970, 1991) explicitly formalized the concept of market efficiency. Fama (1970) states that, 'in an efficient market, prices "fully" reflect all available and relevant information'. In such a market, when new information (news) arrives, security prices quickly and correctly respond to that

[3] The work of Bachelier (1900) was not known until it was appeared in English in Cootner (1964). Osborne (1959) reported similar results as evidenced by Bachelier (1900).

information and incorporate all information at any point of time and reach a new equilibrium. EMH argument is grounded in rational expectation theory. It assumes that investors arrive at rational expectation forecast about future security returns. It can be inferred that when prices reflect available information, prices do not move unless and until new information arrives, which cannot be predicted in a systematic manner. Based on new information prices reach new equilibrium which could not be disturbed without new news. This implies that future prices cannot be predictable based on current available information since prices move randomly in response to such news. Ross (2005) explains that the idea behind EMH is that in a competitive market, security prices are resultants of decisions made by individual agents and prices therefore, depend on information underlying those decisions. An investor whose information is inferior or already possessed by the market, cannot outguess the market.

1.3 Forms of Efficiency

Different forms of efficiency stem from the interpretation of 'fully' and 'available information' found in the definition of market efficiency. Roberts (1959) gave three forms of efficiency, namely, weak form, semi-strong form and strong form.

1.3.1 Weak Form of Efficiency

Weak forms efficiency is one where the information set includes only past sequences of returns. When information instantaneously gets absorbed in current returns, such a mechanism would not ensure consistent abnormal returns.

1.3.2 Semi-strong Form of Efficiency

When information set includes all publicly available information, including past sequences of returns, it is termed as semi-strong efficiency.

1.3.3 Strong Form Efficiency

In this form, the information set includes private or monopolistic information. This form of efficiency asserts that even with monopolistic access to certain information, it is not possible to outguess the market[4].

The efficient market hypothesis has been based on the following assumptions:

- No transaction costs in trading[5]
- Information is freely available to market participants
- All participants are profit seeking maximizing investors
- New information arrives into the market randomly
- All participants are aware of implications of current information

Thus, in a market consisting of rational profit seeking investors and where prices completely incorporate information, it would not be possible to earn excess returns. Under such conditions, a simple buying and holding diversified securities strategy cannot be outperformed by fundamental or technical analysts[6].

A counter theoretical argument to EMH was provided by Grossman and Stiglitz (1980). They argued that informed traders could earn return on their efforts in gathering information as that information enables informed traders to take better positions than others. If EMH holds good, traders could not earn a return on their information. In other words, prices in such market eliminate incentive to collect information as prices aggregate

[4] No-trade theorem argument is that even if one knows what other does not know, then also it is not possible to make profit from such information. A brilliant description of No trade argument and efficient market can be found in Ross (2005).
[5] In empirical testing of EMH, transaction costs are ignored. Now, with screen based trading, transaction costs are considerably minimal.
[6] Malkiel (1973) put it that 'a blindfolded chimpanzee throwing darts at the Wall Street Journal could select a portfolio that would do as well as the experts'.

information perfectly in such markets (Grossman 1976). Extending the noise rational expectation model of Robert Lucas, Grossman and Stiglitz (1980) showed that in an informationally efficient market, information is costly and there would be no reward to collect any sort of information. So in a competitive market, informed traders could stop endeavour of collection of information which is a costly affair. This leads eventually the market to collapse. Market consists of people of different beliefs, and not homogenous participants. Without heterogeneous investors market cannot work. Because market works only when people with different beliefs trade. According to Black (1986), financial market is characterized by noise. Investors trade on noise, thinking that they are trading on information.. It is noise which makes trading possible in financial markets, but it is which makes these market inefficient. Furthermore, price would not reveal all information in the presence of noise and difference in beliefs would not be arbitraged completely (Grossman, 1977). A portfolio strategy ensures strong abnormal profits when overconfidence of investors generates momentum in stock returns (Daniel and Titan, 2000).

1.4 Random Walk Model

Random walk model (RWM) or random walk hypothesis (RWH) has been one of the important and effective models employed to examine the behaviour of stock returns in empirical research. There are various definitions of random walk, but the main contention of random walk is that asset prices move in a random manner.

Let us consider the following equation:

$$\mathrm{R}_t = \delta + R_{t-1} + \varepsilon_t \qquad \ldots (1.1)$$

where R_t is stock returns at time *t* , R_{t-1} is stock returns at time *t-1,* δ is the drift parameter (or expected returns), ε_t is error term. The stochastic variable of stock returns R_t is said to be random walk, with a drift parameter δ, if

$$\varepsilon_t \sim (0, \sigma^2) \qquad \ldots (1.2)$$

where white noise term, ε_t is independent and identically distributed with mean zero and constant variance σ^2. Thus the value of R_t at time *t* is equal to its value at time *t-1* plus a random shock. The important feature of RWM is persistence of random shocks. A particular shock does not die away. If the process $\{\varepsilon_t\}$ in addition to conditions mentioned in equation (1.7), is normally distributed, then it is equivalent to arithmetic Brownian motion (Campbell *et al*, 1997). The independence of increments $\{\varepsilon_t\}$ implies that the process is strictly white noise process. It is a stricter definition of RWH. Campbell, *et al* (1997), in addition to it, defines less restrictive definitions of RWM.

1.4.1 Independent Increments

From time to time, changes in technology, institutions, regulation and market microstructure have been in order. It is difficult to find identical distribution of increments. Independent increments version of RWM is one which requires increments to be independent but not identically distributed. It allows for unconditional heteroscedasticity in ε_t's.

1.4.2 Uncorrelated Increments

By relaxing independence assumption, the uncorrelated increments version of RWM refers to a process with dependent but uncorrelated increments.

1.5 Status of Empirical Work

The EMH is tested empirically by applying various econometric techniques. The most popular test in earlier studies is the serial correlation test. The early works on behaviour of stock returns showed that returns follow a random walk [Kendall, 1953; Roberts, 1959; Osbrone 1959; Working, 1960, Niederhoffer and Osborne, 1966; Jennergeen and Korsvold, 1974]. However, many later studies documented mean-reverting tendency in stock returns [Fama and French, 1988; Poterba and Summers, 1988; Balvers *et al,* 2000]. Anomalies were also reported by Fama (1998). The studies from emerging market also reported mixed evidences. The debate in India too is inconclusive.

1.6 Stock Market Developments and Market Microstructure Changes in India

India being one of the emerging economies has registered a tremendous economic growth in the past decade. Financial sector reforms have been pushed keeping the objective of creating a vibrant financial sector. Indian equity market has made substantial growth on all fronts in recent time.[7] Indian equity market now has the second largest number of listed companies (4,887) and it has secured 8th and 15th position in terms of market capitalization (1,819 billion US dollar) and turnover (1,108 billion US dollar) respectively. Select stock market indicator released by the World Bank (2008) for India shows that total market capitalization as percentage of GDP increased from 56 percent in 2004 to 89 percent in 2006. However, there was marginal decline in turnover ratio during the same period (see table 1.1).

[7] NSE (2008) in its review of capital market provided a detailed discussion on recent developments and achievements of Indian equity market.

The increased percentage of market capitalization to GDP indicates the growing importance of equity market in the economy. All India market capitalization was around US $ 1,288,392 million and trading volume on capital market segment of exchanges was US $ 1,283,667 million at the end of financial year 2008 (NSE, 2008). Nevertheless, the phenomenal growth achieved in the past concentrated in National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). These two exchanges account for 99.99 percent of total turnover during 2007-08. Even the BSE, the oldest stock exchange in Asia accounts just about 9 percent of total turnover (4,234,134 US $ million). It is NSE which is the market leader accounting 90.27 percent of total turnover (456,173 US $ million). In the past decade, with its commencement of business in 1994, NSE emerged as largest stock exchanges in India having 67 percent of share in trading volume.

Several market microstructure changes have been introduced in Indian equity market in the past decade. All 19 stock exchanges in India are now corporatized and demutualized. Fully automated screen based trading system is in place. Now Indian equity market has nationwide network of trading through over 4,000 corporate brokers and about 9487 trading members are registered with Securities and Exchange Board of India (SEBI). An important landmark is establishment of the NSE that started its operation in November, 1994. 'NSE is the first stock exchange in the world to use satellite communication technology for trading' (NSE, 2009). The derivative instruments such as Index Options, Index Futures, Single Stock Futures and individual stock options were introduced at NSE and BSE between 2000-2001 in order to improve risk management and efficiency. During the same period, web-based internet trading was allowed both at NSE and BSE. New indices have been floated and now 10 indices at NSE and 8 indices at BSE are available. Furthermore, both the exchanges floated 12 sectoral indices.

SEBI, the regulatory authority also undertook several regulatory and procedural changes to improve efficiency and protect the interest of investors[8]. The FIIs have been permitted to invest in Indian capital market and SEBI recently approved short selling including for foreign institutional investors (FIIs). Further, SEBI allowed direct market access (DMA)[9]facility for institutional investors. These market microstructure changes and regulatory measures have been initiated with the objective to improve efficiency and transparency in security market in India. Now, India is considered as one of the favoured destinations for investment.

1.7 The Research Problem Defined

The behaviour of stock returns has been extensively debated over the years. Researchers have examined the efficient market and random walk characterization of returns and alternatives to random walk. Linear dependence and non-linear dependence in stock returns ensures potential excess profit opportunities in the market. Mean-reversion is one of the competing alternatives to the random walk. If the returns exhibit a tendency to return to trend path, such tendency is termed as mean-reversion (Fama and French, 1988; Poterba and Summers, 1988). The mean-reversion view contrasts RWH and thus market efficiency.

[8] For detailed information on various regulatory measures initiated by SEBI, see annual reports of SEBI.
[9] DMA allows brokers to offer clients direct access to the exchange trading system through the broker's infrastructure without manual intervention by the broker. This facility is available from April, 2008. see, NSE (2008, 2009).

Another aspect of stock market returns which departs from random walk hypothesis is long memory or long-range dependence. Long memory or long-range dependence is a process in which its autocovariances are not absolutely summable. Long memory implies that the underlying time series realizations are temporally dependent at distant lags. The autocorrelation function of such stationary series decays hyperbolically. This was originally conceived by Hurst (1951). Later, Granger and Joyeux (1980), and Hosking (1981) proposed autoregressive fractionally integrated moving average (ARFIMA) model to examine the issue of long-memory. The persistent temporal dependence between distant observations indicates possibilities of predictability and hence provides opportunity to speculators to forecast future returns based on past information and make abnormal profits. Presence of long memory has important theoretical and practical implications. It violates the efficient market hypothesis. The asset pricing model would also be invalid in the presence of long-memory.

Furthermore, persistence in volatility invalidates market efficiency. The long memory in volatility indicates presence of predictable components and thus provides scope of extra normal returns based on past history of volatility. The conventional models of volatility could not capture such persistence volatility. In the presence of long memory in volatility, those models which use short memory such as derivative pricing, value at risk models would not be reliable.

Against this background and in the context of drastic changes in the economy in general, and market microstructure changes in equity market in India in particular, the present study seeks to examine the issues of market efficiency, long memory and volatility in two premier stock exchanges namely, NSE and BSE in India. Since a study of this kind has not been undertaken in the past, the present study is relevant.

1.8 Objectives of the Study

In the light of the above background, the objectives of the present study are formulated as follows:

i. To empirically investigate stock returns behaviour by testing validity of random walk hypothesis
ii. To understand non-linear dependent structure in underlying stock returns and explain how such a phenomenon contradicts efficient market hypothesis
iii. To check whether stock returns exhibit a mean-reverting tendency and also address the issue of accounting for structural breaks
iv. To detect long memory or long-range dependence originally conceived by Hurst (1951) and later developed and applied in Economics by Granger and Joyeux (1980), and Hosking (1981)
v. To detect long memory in volatility following Baillie *et al* (1996) procedure.

1.9 Justification of the Study

The study is justified for the following reasons. First, the available studies refer to the 1980's and early 1990's and hence could not capture the nature of microstructure of Indian stock markets which has undergone various changes in the initial years of 21st century. This study uses new and disaggregate data covering the period of such structural changes is in order. Second, earlier studies in India focused only on BSE and (mostly confined to BSE Sensex index) with the belief that every other stock exchange in India follows BSE. However, in last few years, NSE emerged as a largest stock exchange in India. Third, the data set of 14 indices which the present study used, has another advantage as it helps to measure relative efficiency of markets represented by different indices traded at the same exchange. It also helps to understand how stock returns of highly liquid and less liquid indices behave. Fourth, studies in India used mostly conventional tests to examine the issue of market efficiency. The present study has employed certain state of the art tests which are first of their kind in the Indian context. Finally, the issue of non-linearity, long-range dependence and long memory in volatility have been seldom addressed in the previous studies in the context of Indian equity market.

1.10 Research Methodology

The primary aim of the present study is to investigate behaviour of stock returns in Indian equity market. A brief outline of methodology followed is presented here. Detailed discussion of methodology is carried out in relevant chapters.

Various parametric and non-parametric tests have been employed to test linear dependence in stock returns. To test whether stock returns are generated by a random walk process, where increments are expected to be independent and identically distributed, autocorrelation test is employed. The Ljung and Box (1978) portmanteau Q-statistic is used to test the joint hypothesis that all autocorrelation coefficients are simultaneously equal to zero. Individual variance ratio test due to Lo and MacKinlay (1988) which is capable of distinguishing several competing alternative hypotheses and, to avoid size distortion problem, Chow and Denning (1993) tests are performed. Non-parametric test are appropriate when stock returns are not normally distributed. Runs test, Brock *et al* (1996) test which is popularly known as BDS test, portmanteau test for time based dependence in a series are conducted. Non-parametric variance ratio test based on ranks and signs proposed by Wright (2000) is also employed to shed further light,

Non-linear dependence in stock returns indicates possibility of predictability and thus violates notion of market efficiency. In this context, a set of non-linearity tests is applied to uncover non-linear dependence in underlying stock returns. The tests employed in the study have different power against different forms of non-linear process. The tests are implemented on residuals extracted after removing linear dependence in daily returns by fitting an AR (ρ) model.

The conventional unit root tests namely, augmented Dickey and Fuller (1979) and Phillips and Perron (1988) (PP) have been employed to investigate the issue of mean-reversion as an alternative to RWH. Perron (1989) showed that ignoring structural break in unit root test leads to spurious results. Considering the importance of structural breaks, Zivot and Andrews (1992) sequential single break test and two break test proposed by Lee and Strazicich (2003) that incorporates structural breaks in both null and alternative hypothesis are utilized. Both these two test searches for break/s endogenously. The former allows single break each in mean and intercept, while the latter test allows for each of two breaks in mean and shift.

Autoregressive fractionally integrated moving average (ARFIMA) model of Granger and Joyeux (1980), and Hosking (1981) is utilized to analyze the issue of long memory pattern in returns series. Geweke and Porter-Hudak's (1983) semiparametric approach, Gaussian semiparametric test proposed by Robinson (1995) and a bias reduced log periodogram estimator of Andrews and Guggenberger (2003) are utilized to detect long memory in level of stock returns.

Recent international studies have provided evidence of long memory in returns volatility. The conventional ARCH models cannot capture the slow decay of autocorrelation function in conditional variance. Keeping this in mind, the present study has a model of Baillie *et al* (1996) to capture very slow hyperbolic decay in the autocorrelations of the volatility process. For a comparison purpose, GARCH and IGARCH models are also estimated.

1.11 Nature and Sources of Data

Data of daily values[10] of 8 indices from NSE and 6 indices from BSE for the period January 2, 1997 to March 31, 2009 are considered for the study. This large and varied data sample is expected to reflect drastic changes taken place in Indian equity market. The data range is different for different indices, as shown in table 1.2. The launching of different indices at different point of time by the exchanges dictated the different sample range. However, these indices have at least 5 years of track record thus providing enough number of observations to perform powerful tests and accurate estimation[11]. Indices namely, CNX Nifty, CNX Nifty Junior, CNX Defty CNX 100, CNX 500 are considered from NSE; Indices chosen from BSE are: BSE Sensex, BSE 100, BSE 200, BSE 500, BSE Midcap and BSE Smallcap. Considering the growing importance of information technology, banking and infrastructure sectors in the economy, respective indices of these sectors from

[10] Taylor (2005) suggests that time interval between prices should be sufficient enough so that trade takes place in most intervals. Selecting daily values will be both appropriate and convenient.
[11] Taylor (2005) opines that at least four years of daily values (more than 1000) observation are required to obtain interesting results.

NSE namely, CNX IT, CNX Bank Nifty and CNX Infrastructure are also added. The daily index values of the NSE and BSE are collected from official website of NSE, www.nseindia.com and CMIE Prowess respectively. A brief description of selected indices is as follows:

BSE Sensex

BSE Sensex represents large and financially sound 30 companies across key sectors. It accounts for about 45 percent of total market capitalization on BSE.

BSE 100[12]

BSE 100 index is made up of 100 companies listed on 5 important stock exchanges in India. The scripts included are of those companies that have been traded more than 95 percent trading days and figured in final 200 ranking[13]. BSE 100 stocks represent about 73 percent of market capitalization.

BSE 200

Equity shares of 200 selected companies from the specified and non-specified lists of BSE constitute BSE 200 index. It represents 82.70 percent of market capitalization on BSE.

BSE 500

BSE 500 constitutes about 94 percent of market capitalization on BSE. It covers major 20 industries of the company. The stocks which are included in BSE 500 are those which have traded 75 per cent days and figured in top 750 companies in final ranking.

BSE Midcap

This index constitutes medium sized stocks and represent about 16 percent of total market capitalization on BSE.

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[12] BSE 100 was formerly known as BSE National Index.

[13] BSE arrives at this ranking base on three months full market capitalization of stock and liquidity which are given 75 and 25 percentage of weight respectively.

BSE Smallcap

It accounts for about 6 percent of market capitalization and made up of small sized stocks.

CNX Nifty

It represents most liquid and well diversified 50 stocks traded at NSE representing 22 sectors of the economy. Its percentage to total market capitalization is about 65 percent on NSE.

CNX Defty

CNX Defty is nothing but CNX Nifty, measured in dollars. This index is to facilitate FIIs and off-shore fund enterprises.

CNX Nifty Junior

CNX Nifty Junior consists of next 50 liquid stocks excluded from CNX Nifty and represents about 10 percent of total market capitalization on NSE.

CNX 100

Diversified 100 stocks representing 35 sectors of the economy constitute CNX 100 index. It represents 75 percent of total market capitalization on NSE

CNX 500

CNX 500 equity index is broad based index and accounts 95 percent of total market capitalization. The companies included are disaggregated into 72 industry indices.

CNX IT

Companies that have more than 50 percent of their turnover from IT related activities are compressed in CNX IT. The CNX IT Index stocks represent about 80.33 percent of the total market capitalization of the IT sector as on March 31, 2009. Companies included in

CNX IT have at least 90 percent trading days and ranked less than 500 based on market capitalization. This index accounts 14 percent of total market capitalization on NSE.

CNX Bank Nifty

The most liquid and large market capitalized 12 Indian Banking stocks traded on NSE comprises CNX Bank Nifty. The CNX Bank Index stocks represent about 87.24 percent of the total market capitalization of the banking sector and about 8 percent of the total market capitalization on NSE.

CNX Infrastructure

CNX Infrastructure index includes 25 stocks of companies belonging to Telecom, Power, Port, Air, Roads, Railways, shipping and other Utility Services providers. CNX Infrastructure Index constituents represent about 21.43 percent of the total market capitalization on NSE.

1.12 Organization of the Thesis

The thesis is organized into six chapters

The first chapter recapitulates the basic tenets and brief history of theory of market efficiency. It also includes problem identification, nature and sources of sample data, justification for and methodology of the study. The second chapter provides evidence from parametric and non-parametric tests of random walk hypothesis. In the third chapter, the non-linear paradigm is discussed. Results from a set of non-linearity tests are discussed. The fourth chapter treats the issue of mean-reversion and structural breaks with empirical evidences. The issue of long memory in returns is examined in the fifth chapter. The sixth and final chapter explains the long memory in volatility followed by presentation of summary, major findings and implications of the study.

Table 1.1: Select Stock Market Indicators for India

Indicators	2004	2005	2006
Market Capitalization as % of GDP	56.1	68.6	89.8
Turnover Ratio (%)	115.5	93.6	96.4
Listed Companies	4,730	4,763	4,796

Source: World Development Indicators - 2008

Table 1.2 Data Sample

Sl. No	Index	Time Period	% of Total Market Capitalization
01	CNX Nifty	02/06/1997 – 31/03/2009	65.34
02	CNX Junior	02/06/1997 – 31/03/2009	9.89
03	CNX Defty	02/06/1997 – 31/03/2009	-
04	CNX IT	02/06/1997 – 31/03/2009	6.97
05	BSE Sensex	01/01/1998 – 31/03/2009	46.53
06	BSE 100	01/01/1998 – 31/03/2009	75.67
07	BSE 200	01/01/1998 – 31/03/2009	85.24
08	CNX 500	07/06/1999 – 31/03/2009	95.11
09	CNX Bank Nifty	01/01/2000 – 31/03/2009	7.74
10	BSE 500	03/01/2000 – 31/03/2009	93.51
11	CNX 100	01/01/2003 – 31/03/2009	75.24
12	CNX Infrastructure	01/01/2004 – 31/03/2009	21.43
13	BSE Midcap	01/01/2004 – 31/03/2009	12.80
14	BSE Smallcap	01/01/2004 – 31/03/2009	3.7

Note: % of total market capitalization is as on March 31, 2009. Indices are arranged according to number of observation in descending order.

CHAPTER - 2

RANDOM WALK CHARACTERISTICS OF STOCK RETURNS

2.1 Introduction

The behaviour of stock returns has been extensively debated over the years. Researchers have examined the efficient market and random walk characterization of returns and alternatives to random walk. In an efficient market, current prices quickly absorb information. Such mechanism does not provide scope for any investor to make abnormal returns (Fama, 1970). In respect of empirical evidences, the early studies have found evidences in favour of random walk hypothesis (RWH). In later period, however, studies have supported mean reversion in returns. Anomalies have also been observed in empirical research (Fama, 1998). Fama's model is criticized for its assumption that market participants arrive at a rational expectations forecast. It is argued that trade implies heterogeneity (bull and bear traders) and therefore returns can be predicted. Further, elements of psychological and behavioral in stock price determination help to predict the future prices. In contrast to Fama's model, Campbell *et al (*1997) states that asset returns are predictable to some degree. Consensus on this issue thus continues to be elusive. In this context, an attempt is made to empirically check whether stock returns in India follow a random walk or not. The specific focus of the present chapter is to test linear dependence or lack of it in stock returns on NSE and BSE.

2.2 Review of Previous Work

Literature on random walk and market efficiency hypothesis has been truly abundant. Here an attempt is made to present a brief review of previous work[14]. Bachelier (1900) is perhaps the first who theorized the concept of market efficiency. The seminal works of Samuelson (1965) and Fama (1965, 1970) triggered much interest in this area.

The studies of Working (1960), Fama (1965), Niederhoffer and Osborne (1966) suggested that stock price movements are not serially correlated and therefore, it is impossible to make abnormal profits from random investment. Similar results were reported by Jennergeen and Korsvold (1974) in their study of Norwegian and Swedish markets. Contrary to these findings, Solnik (1973) observed more apparent deviations from random walk in European markets. French and Roll (1986) observed statistically significant negative serial correlation in daily returns even though they were skeptical about the economic significance of such returns. In a similar vein, Keim and Stambaugh (1986) found statistically significant predictability in stock prices by using forecasts of predetermined variables. Interestingly, Fama and French (1988) cast doubts on the validity of RWH showing that long horizon returns are negatively correlated (mean-reversion). Jagadeesh (1990) reported positive serial correlation for long horizons. Frennberg and Hansson (1993) for Sweden found dependence in stock returns.

The early studies on market efficiency used serial correlation, runs and spectral tests to examine the issue of random walk. The conventional techniques, such as serial correlation seem to suffer from restrictive assumptions. They tend to be less efficient to

[14] For an excellent review on market efficiency, see Fama (1970)

capture the patterns in returns. The most popular test of random walk since the publication of Lo and MacKinlay (1988) is the variance ratio test (henceforth, LMVR). In their study of weekly stock returns in the US, Lo and MacKinay (1988) rejected earlier evidence in favour of random walk characterization of returns. Gilmour and McManus (2001) applied LMVR and model comparison tests on Central European Markets namely, Czech Republic, Hungary and Poland. While the former test provides empirical evidence of random walk, the latter test rejects the same. According to the study, inconsistency in results is due to particular martingale process of random walk. Evidences from Russian stock market supported random walk for monthly data (Dissanaik and Linowski, 2005). Largely, evidences, though diverse, indicate random walk behaviour of stock returns.

Emerging and developing markets because of under-development of markets, and several frictions, are expected to strongly reject random walk process of underlying returns (Harvey, 1993). Studies from the emerging markets also have thrown inconsistent evidences. Butler and Malaikah (1992) empirically concluded that returns in Kuwait followed a random walk while Saudi did not. Abraham *et al* (2002) who applied LMVR on emerging markets observed dependencies in returns at index values for Saudi Arabia, Kuwait and Bahrain. However, the corrected returns are in support of weak form of market efficiency. Rejection of random walk in Middle East markets has been identified to be the result of thin and infrequent trading (Butler and Malaikah, 1992; Abraham *et al,* 2002).

Non-random walk behaviour of stock returns is not confined to emerging Middle East markets. Such behaviour has also been found in other emerging markets too. Dias *et al* (2002) who performed LMVR with other conventional tests on returns in Portuguese market showed dependencies in return series. Smith and Ryoo (2003) by and large found evidences against RWH in markets of 17 emerging economies and 4 European economies. Urrutia (1995) found 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 found mixed results. The former found evidence in support of random walk for Latin America. The latter study, however, found significant autocorrelation in Mexican market and random walk behviour in Brazilian market.

The Asian emerging markets also showed mixed results. Huang (1995), Alam *et al* (1999) and Chaing *et al* (2000) found that emerging Asian markets, were not efficient. Supporting these findings, Husain (1997) concluded that random walk was not valid in Pakistan's equity markets because of presence of strong dependence of stock returns. However, not agreeing with these findings, Cooray (2004) who employed unit root, autocorrelation and spectral test empirically evidenced that South Asian markets such as India, Bangladesh, Pakistan and Sri Lanka followed a random walk. Thin trading, as in case of Middle East markets, was found to be one of the important sources of significant correlation in returns (Mustafa and Nishat, 2003). Empirical findings on China are quite consistent. Liu *et al* (1997) in a study reported that Chinese markets were efficient. Darant and Zhong (2000) and Lee *et al* (2001) reported independence of returns series for Chinese market. Conflicting results in the same market were observed by Lima and Tabak (2004). While the Chinese - A[15] shares and Singapore stock market were weak form efficient, the Chinese - B shares and Hong Kong market revealed autocorrelation in

[15] 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.

returns. The market capitalization and liquidity could explain such conflicting trends as the authors noted. The empirical findings of Lock (2007a) Charles and Darne (2008) and, Fifield and Jetty (2008) supported the earlier evidences on China that Share A share was weak form efficient while Share B evidenced against it. Eitelman and Vitanz (2008) who employed variance ratio test for 44 emerging and industrialized economies pointed out that the markets with poorer risk-adjusted performance were more likely to reject random walk than better performing markets.

The LMVR tests individual variance ratios for a specific aggregation investment horizon. This may result in size distortions. In order to overcome such deficiency in LMVR, recent studies employed Chow and Denning (1993) multiple variance ratio test along with other tests. The studies of Ayadi and Pyun (1994) for Korea and Worthington and Higgs (2003) for Latin America reported dependencies in returns. Huber (1995) examined the Vienna stock exchange and concluded that random walk is rejected at highly significant level for daily returns in Vienna. However, individual stocks seemed to follow a random walk. Thus, the thinness of market could lead to rejection of random walk. Ryoo and Smith (2002) showed evidence against random walk in Korean market. Smith (2007) who investigated whether Middle East stock markets follow a random walk or not found that largely Israeli, Jordanian, Lebanese markets were weak form efficient while Kuwait and Oman markets rejected RWH. Smith *et al* (2002) reported autocorrelation in returns of Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria and Zimbabwe. It is only in South Africa, the study found empirical evidence in support of random walk.

The empirical evidence for Australia for the longer period namely, 1875-2004 provided by Worthington and Higgs (2009) rejected the random walk thus, revealing strong serial dependence in the stock returns. Hoque *et al* (2007) also observed evidences rejecting RWH in the majority of eight emerging markets. Borges's (2007) findings from multiple variance ratio tests corroborated the earlier findings of Dias *et al* (2002), and Worthington and Higgs (2004) that Portuguese stock returns were highly correlated. With multiple variance tests, an attempt is made to unmask sectoral efficiency of economies namely, Jordan, Qatar, Saudi Arabia and United Arab Emirates. The study obtained inconsistent results among different sectors and different economies (Benjelloun and Squalli, 2008). The EMH in European stock market was investigated by Borges (2008). 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, U.K and Spain followed a random walk, there existed positive serial correlation in returns of Greece and Portugal. Nakamura and Small (2007) by using a new method namely, small-shuffle surrogate (SSS) method concluded that the US and Japanese markets supported RWH. Similar were the findings of Lock (2007b) for Taiwan market.

The quest for study of stock market efficiency in India began with early work of Krishna 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 in the BSE followed RWH. Similar evidences of random walk behaviour for stock returns also were noted by Barua (1981), Gupta (1985) and Chawla *et al* (2006)[16]. Furthermore, in their examination of stock returns behaviour on BSE Sensex, BSE National Index (now, BSE 100), and 53 individual stocks, Amanulla (1997), Amanulla and Kamaiah (1998), in addition to serial correlation and rank correlation tests, used ARIMA

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[16] Amanullah and Kamaiah (1996) presented an excellent and comprehensive review of Indian evidences on market efficiency. Also see, Barua (1994).

(0, 1, 0) model to examine distribution pattern of increments which received less focus on weak form efficiency studies in India. They concluded that equity market in India was weak form efficient. Findings by recent studies which have employed various tests such as unit root tests, neural network, BDS test to examine the issue of random walk [e.g Mitra, 2000; Poshakwale, 2002; Ahmad *et al* 2006] evidenced rejection of random walk characterization of stock returns in India. 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 yield different results. The empirical results of various studies appear to be sensitive to the tests employed for the analysis. However, broadly, the conventional parametric tests provide evidence in support of random walk while non-parametric tests, such as BDS overwhelmingly reject independence of returns. Thin trading or non-synchronous trading, various restrictions and incomplete reforms are cited as important factors for rejection of random walk characterization of returns in emerging markets. The review of literature provides mixed results regarding the returns behaviour.

2.3 Weak Form Efficiency: Empirical Tests

2.3.1Parametric 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 evaluate whether successive values of serial correlation is significantly different from zero. To test the joint hypothesis that all autocorrelation coefficients, ρ_k are simultaneously equal to zero, Ljung-Box (1978) portmanteau Q-statistic is used in the study. The test statistic is defined as

$$LB = n(n+2)\sum_{k=1}^{\mathrm{m}}\left(\frac{\hat{\rho}_{\mathrm{k}}^2}{\mathrm{n}-k}\right) \qquad \ldots (2.1)$$

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[17]

Lo and MacKinaly (1988) proposed variance ratio test which is capable of distinguishing among several interesting alternative stochastic process. 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

$$\mathrm{r}_t = \mu + \ln\mathrm{P}_t - \mathrm{P}_{t-1} + \varepsilon_t \qquad \ldots (2.2)$$

where r_t is stock returns, μ is drift parameter $\ln\mathrm{r}_t$ 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, $\mathrm{r}_t(2) \equiv \mathrm{r}_t - \mathrm{r}_{t-1}$, to twice the variance of a one-period return r_t. Then variance ratio VR (2) is

[17] An excellent discussion on the test and its empirical application can be seen in Campbell *et al* (1997).

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

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

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

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 q period variance ratio satisfies the following relation:

$$\mathrm{VR}\,(q) = \frac{\mathrm{Var}\,[\mathrm{r_t}\,(q)]}{q.\mathrm{Var}\,[\mathrm{r_t}]} = 1 + 2\sum_{k=1}^{\mathrm{q}-1}\left(1-\frac{\mathrm{k}}{q}\right)\ \rho^{\mathrm{k}} \qquad \ldots (2.4)$$

where $\mathrm{r}_t(k) \equiv \mathrm{r}_t + \mathrm{r}_{t-1} + \cdots + \mathrm{r}_{t-k+1}$ and $\rho(k)$ is the k^{th} order autocorrelation coefficient of $\{\mathrm{r}_t\}$. Equation (2.4) shows that at all q, VR(q) = 1. For all definition of random walk (defined in chapter 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[18] under the null hypothesis of homoscedastic increments and VR (q) =1, test statistic Z (q) is given by

$$\mathrm{Z}(q) = \frac{\mathrm{VR}\,(q)-1}{\phi\,(q)^{1/2}} \qquad \ldots (2.5)$$

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

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

In the equation (2.5), asymptotic variance $\phi(q)$ is defined as

$$\phi(q) = \left(\frac{2(2q-1)(q-1}{3q}\right)^2 \qquad \ldots (2.6)$$

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

$$Z^*(q) = \frac{\text{VR}\,(q)-1}{\phi^*(q)^{1\backslash 2}} \qquad \ldots (2.7)$$

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

$$\phi^*(q) = \sum_{j=1}^{q-1} \left(\frac{2(2q-1)}{q}\right)^2 \delta(j) \qquad \ldots (2.8)$$

where

$$\delta(j) = \frac{\sum_{t=j+1}^{nq} (r_t-\hat{\mu})^2 \, (r_{t-j}-\hat{\mu})^2}{[\sum_{t=1}^{nq} (r_t-\hat{\mu})^2]^2} \qquad \ldots (2.9)$$

Thus, according to variance ratio test, returns process is a random walk when variance ratio at a holding period q is expected to be unity. If it is less than unity, implies negative autocorrelation (mean-reversion) 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. So 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 random walk hypothesis 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. It ignores joint nature of random walk. To overcome this problem, Chow and Denning (1993) propose 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, $M_r = (q_i) = VR\,(q) - 1 = 0$. This can be generalized to a set of m variance ratio tests as

$$\{\, \mathrm{M}_r\,(q_i) |\, i = 1,2 \dots, m \,\} \qquad \dots (2.10)$$

Under RWH, multiple and alternative hypotheses are as follows

$$\mathrm{H}_{0i} = \mathrm{M}_r = 0 \text{ for } i = 1,2, \dots, m \qquad \dots (2.11a)$$

$$\mathrm{H}_{1i} = \mathrm{M}_r\,(q_i) \neq 0 \text{ for any } i = 1,2, \dots, m \qquad \dots (2.11b)$$

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

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

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

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

where $\mathrm{Z}^*(q_i)$ is defined as in equation (2.7). Random walk is rejected if values of standardized test statistic, CD_{12} or CD_2 is greater than the SMM critical values at chosen significance level.

2.3.2 Nonparametric Tests

2.3.2.1 Runs Test

Runs test is one of the extensively used non-parametric tests of random walk. 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 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

$$\mathrm{ER} = \frac{\mathrm{X}(\mathrm{X}-1) - \sum_{i=1}^{3} \mathrm{c}_i^2}{\mathrm{X}} \qquad \text{. . . (2.14)}$$

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 equation (2.14) has an approximate normal distribution for large X. Hence, to test null hypothesis, standard Z statistic can be used[19].

2.3.2.2 *BDS Test*

The BDS test developed by Brock *et al* (1996) is a portmanteau test for time based dependence in a series. It can be used for testing against a variety of possible deviations from independence including linear dependence, non-linear dependence, or chaos. BDS test uses correlation dimension of Grassberger and Procaccia (1983). Following Taylor (2005), to perform the test 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, ε) is estimated by

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

$$I_m\,(x_s, x_t, \varepsilon\,) = \prod_{k=0}^{m-1} I\,(x_{s+k}\,, x_{t+k}, \varepsilon\,), \qquad \ldots (2.15)$$

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

The function I (·) indicates whether or not the observations at times *s* and *t* are near each other, as determined by the distance ε. The product I_m (·) 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 histories that are near each other. For observations from many processes, limit is defined as

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

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[19] Further discussion about the runs test may be found in Siegel (1956).

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

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

BDS considered 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.

$$W_m(\varepsilon) = \sqrt{\frac{n}{\hat{V}_m}}\left(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m\right) \qquad \text{. . . (2.16)}$$

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

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

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

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

It has power against a variety of possible deviations from independence including linear dependence, non-linear dependence, or chaos. The BDS statistics is commonly estimated at different m, and ε.

2.4 Empirical Results

This section discusses the empirical results of parametric and non-parametric tests of weak form of efficiency which are carried out in the present study.

The descriptive statistics for the 14 indices are given in table 2.1. The highest average returns are registered by CNX 100. This is followed by CNX Infrastructure. This reflects the performance of this index owing to considerable growth of infrastructure sector in India. This also indicates that the small size indices commonly have higher returns. CNX Bank Nifty is the other index which shows higher mean returns. However, the CNX 500 register negative mean returns. Further, the BSE 200 has the highest standard deviation, followed by CNX IT indicating high volatility, and lowest is of CNX Nifty and BSE Sensex (see table 2.1). The returns of all indices are negatively skewed implying the returns are flatter to the left compared to normal distribution. The significant kurtosis indicates that stock returns are leptokurtic, that is, returns have fatter tails than a normal distribution. Further, significant Jarque-Bera statistic rejects the null of normality and thus confirming that stocks returns are non-normally distributed. This confirms the stylized fact of recent financial data.

The present study employs Ljung-Box test to check whether all autocorrelations are simultaneously equal to zero. The plot of autocorrelation function of indices given in figure 2.1 clearly shows that autocorrelations even up to 15 lags are significant. The Ljung-Box test statistics are provided in table 2.2**.** It is evident from the table that CNX IT, CNX 500, indicate random walk where the null hypothesis of no serial correlation cannot be rejected at conventional significance level. For other indices, null is rejected as the p value is almost zero indicating autocorrelation in returns.

Lo-MacKinlay variance ratios and corresponding homscadasticity and hetroscadasticity robust test statistic for various investment horizons like 2, 4, 8, and 16 are presented in second and third row respectively in table 2.3. It is evident from the table that with the sole exception of BSE 100, variance ratios for all other indices at all investment horizons are greater than unity. The variance ratio tests offer conflicting results. Significant homoscedastic and heteroscedastic statistics reject RWH for the indices 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 ratio for Nifty Junior, BSE Midcap, BSE Smallcap, CNX 500 and BSE 500 is greater than unity, indicating the presence of significant positive autocorrelations. However, the statistic for CNX IT and the BSE 200, BSE Sensex supports the presence of random walk as value of test statistic is lower than critical value. Volatility change over time and therefore rejection of null of variance ratio equal to unity due to conditional heteroscedasticity is not of much interest. The homoscedastic statistic given in second row in table 2.3 for CNX Nifty, CNX Infrastructure at lag 2, CNX Defty, CNX 100 at lag 2 and 4, and for BSE 100 at all investment horizons rejects RWH. But, 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.

The conflicting results from the LMVR test reveals the fact that the individual variance ratio tests of LMVR do not give consistent evidences 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 Chow and Denning (1993) maximum heteroscadasticity robust statistic is given in last column of table 2.3. It is evident from the table that CNX Nifty Junior, CNX 500, CNX Bank Nifty, BSE 500, BSE Midcap and BSE Smallcap resoundingly reject the null of random walk. It is to be noted that LMVR test also rejects null of RWH for these indices. On the other hand, return indices such as CNX Nifty, CNX Defty, CNX IT, BSE Sensex, BSE 100, BSE 200, CNX100, CNX Infrastructure, validate RWH as the Chow-Denning statistic values are less than the critical values. This supports the results of LMVR heteroscedastic test results. Furthermore, Chow-Denning results are not significantly different from those of LMVR. However, conflicting results and statistical size distortion problem can be mitigated by Chow-Denning test and therefore it is preferable in case of mixed results from LMVR.

It may be noted that 5 out of 8 indices traded at NSE and 3 out of 6 indices traded at BSE support RWH. This indicates inter market and intra market variations in the behaviour of stock returns. The parametric tests provided diverse results.

The present study also employs two non-parametric tests namely, the runs test and BDS test. The choice of the tests is appropriate especially in the light of the observation that returns series are non-normally distributed. Sample indices, in the present study, are shown to be asymptotically non-normal (see table 2.1). The runs test is a popular non-parametric test of random walk. Table 2.4 provides runs test statistics. Actual runs (see, third column of table 2.1) are number of change in returns, positive or negative, observed in the returns series. The expected runs given in fourth 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 return indices 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 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 exceeds the expected number of runs. The positive sign of Z statistic implies the negative correlation. With the sole exception of CNX 100, the hypothesis of random walk has been rejected by all the indices.

The BDS test is performed at various embedded dimensions (*m*) like 2, 4, 6, 8, and 10 and also at various distances like 0.5s, 0.75s, 1s, 1.25s and 1.5s where s denotes the standard deviation of the return. BDS test-statistic followed by p-values in parentheses is furnished in table 2.5. The BDS tests the null hypothesis that return series are i.i.d. Rejection of the null hypothesis implies that random walk hypothesis does not pass the test. It is very clear from the results that BDS test rejects the null hypothesis of independence and thereby random walk hypothesis too for all the 14 indices. It shows that returns are dependent. The dependencies may be linear or non-linear in the returns series.

The BDS test has been known to be more powerful than the runs test as the latter suffers from a reduction in test power due to loss of information in the transformation from returns to their signs. On the whole, the results of the runs and BDS test rejected the null of i.i.d (the stricter definition of random walk) at significant level.

2.5 Alternative Variance Ratio Tests

2.5.1 Background

Various tests have been employed to confirm the random walk behaviour of stock returns. The variance ratio test proposed by Lo and MacKinlay (1988) is one of the most popular tests. The test is capable of distinguishing among several interesting and competing alternative hypotheses. The test uses the fact that, if returns are i.i.d then the variance of *k*-period returns is simply the variance of the one period return. Since the publication of Lo and MacKinlay (1988), numerous studies have employed the LMVR test (Ojah and Karemera, 1999; Grieb and Reyes, 1999; Darrat and Zhong, 2000; Dias *et al*, 2002; Al-Khazali *et al*, 2007; Eitelman and Vitanza, 2008; Fifield and Jetty, 2008). The LMVR test, however, is an asymptotic test, whose sampling distribution in finite samples is approximated by their limiting distribution. The test shows severe bias and right skewness leading to serious size distortions. For mean-reverting alternatives, the LMVR test is found to be inconsistent (Deo and Richardson, 2003). In small samples, size distortion problem may be more severe. Further, the test assumes that returns are normally distributed which of late, is quite uncommon in case of financial returns.

An alternative variance ratio test using ranks and signs has been proposed by Wright (2000). The test is more powerful than the LMVR test because of the following two reasons: First, it does not rely on approximate sampling distribution as in case of LMVR. Because, it is possible to compute their exact distribution as the test is based on ranks and signs. Wright (2000) pointed that ‘there is no need to worry about size distortions when using such a test’. Secondly, the test is a non-parametric test, and therefore more appropriate (powerful) if the returns are highly non-normal. Considering its appealing features, the recent studies have employed Wright's (2000) ranks and signs variance ratio test (WRSVR) to examine the issue of weak form market efficiency.

Ma and Barnes (2001) performed this test on Shenzhen and Shanghai stock exchanges in China and found that individual shares were more efficient than indices. Buguk and Brorsen (2003) reported inconsistent results for different *k* values (holding periods) for Istanbul stock exchange (Turkey). Using WRSVR test, Belaire-Franch and Opong (2005) attempted to present some evidence on anomalies. The study refuted RWH for FTSE 100, FTSE 250, FTSE 350 and FTSE All Shares. However, they pointed that the rejection of RWH for indices having higher market capitalization and liquidity was relatively less than their lower counterparts. This view was further supported by Hung *et al* (2009). The WRSVR test was employed to test the efficiency of TOPIX and FTSE exchanges. Based on test results, they concluded that larger cap index for both the exchanges were relatively more efficient than the smaller cap indexes.

In a similar fashion, Segot and Lucey (2005) assessed market efficiency of Middle East and North Africa (MENA) markets[20]. It was observed that small markets such as Tunisia and Jordon empirically proved to be inefficient whereas Israel and Turkey were weak form efficient. In a reply to this, Al-Khazali *et al* (2007) empirically showed that the MENA markets (Beharain, Egypt, Jordon, Kuwait, Morocco, Oman, Saudi Arabia and Tunisia) were weak form efficient. The earlier rejection of weak form efficiency, the study argues, has been because of thin and infrequent trading. The study applied WRSVR test after correcting for thin and infrequent trading and found that the MENA markets were weak form efficient. This view has drawn further support from the study of Hoque *et al*

[20] The selected MENA markets are Morocco, Tunisia, Egypt, Lebanon, Jordon, Turkey and Israel.

(2007) which concluded that thin trading has been one of the important factors responsible for rejection of RWH in emerging markets. Further, Hoque *et al* (2007) pointed out that information asymmetry and lack of well developed financial institutions were the other reasons for such a rejection. Based on WRSVR test results, the study concluded that astute investors could exploit the emerging markets as their stock returns are inter-temporally predictable. The stock exchanges of Barbados, Jamaica, Trinidad and Tobago and CARICOM Regional exchanges were found to be inefficient (Watson, 2009)[21].

Substantial evidence against RWH for 139 Italian stocks was found in a study by Lamonica (2007), who noted that as the *k* value increases, random walk behaviour becomes increasingly evident. For Chinese markets, studies by Fifield and Jetty (2008), and Zhang and Xindan (2008), and Hung (2009) documented that Chinese Share A was relatively more efficient than Share B. However, these studies also noted that the efficiency improved for both the shares due to deregulation, liberalization and improved liquidity. The hypothesis that liquidity improves market efficiency found further empirical support from Hung *et al* (2009).

The evidences from the WRSVR test for various markets showed that most of the markets did not follow random walk. The rejection of RWH is more evident in the conventional LMVR test. The studies from emerging markets indicated higher rejection in case of these markets compared to their developed counterparts. The thinness of markets and infrequent trading, and lack of well developed markets are cited as factors responsible for such rejection. The studies for Chinese markets indicated improvement in efficiency as

[21] CARICOM is a Caribbean Community and Common Market consisting 14 countries.

liberalization process was set in. Further, it is observed from the foregoing discussion that small and less liquid indices are more likely to reject RWH than highly liquid indices.

In this backdrop, it is important to probe into issue of behaviour of stock returns using non-parametric WRSVR test. The existing studies in India have not applied this test. A brief description of the test is given in sub-section 2.5.2 and evidence for India are presented in sub-section 2.5.3

2.5.2 Ranks and Signs Variance Ratio Test

Wright (2000) proposed ranks (R_1 and R_2) and sings (S_1 and S_2) based variance ratio test. He demonstrated that his non-parametric test has better and more powerful properties than conventional variance ratio test. Let r(y_t) be the rank of y_t among y_t. . . y_r. Define,

$$r_{1t} = \frac{\left(\mathrm{r}\ (\mathrm{y_t}) - \frac{\mathrm{T+1}}{2}\right)}{\sqrt{\frac{\mathrm{T+1\ (T+1)}}{12}}} \qquad \ldots (2.19)$$

Under the null hypothesis that y_t is generated from i.i.d sequence, r (y_t) is random permutation of the number of 1 . . ., T with equal probability. Wright (2000) proposes the statistics

$$R_1 = \left(\frac{\frac{1}{\mathrm{T}k} \sum_{\mathrm{t}=k+1}^{\mathrm{T}} (\mathrm{r}_{1t}+\mathrm{r}_{1t-1} \ldots + \mathrm{r}_{1\mathrm{t}-k})^2}{\frac{1}{\mathrm{T}} \sum_{\mathrm{t}=1}^{T} r_{1t}^2} - 1\right) \left(\frac{2(2k-1)\,(k-1)}{3k\mathrm{T}}\right)^{-1/2} \qquad \ldots (2.20)$$

which follows an exact sampling distribution. Further, he proposes use of alternative standardization

$$r_{2t} = \Phi^{-1}\left(\frac{r\ (y_t)}{\mathrm{T+1}}\right) \qquad \ldots (2.21)$$

In equation (2.21), Φ is the standard normal cumulative distribution function. This gives rise to the R_2 statistics as given in equation (2.22):

$$R_2 = \left(\frac{\frac{1}{Tk} \sum_{t=k+1}^{T} (r_{2t}+r_{2t-1} \ldots + r_{2t-k})^2}{\frac{1}{T} \sum_{t=1}^{T} r_{2t}^2} - 1 \right) \left(\frac{2(2k-1)(k-1)}{3kT} \right)^{-1/2} \qquad \ldots (2.22)$$

The R_2 test shares the same sampling distribution as R_1. The critical values of these tests can be obtained by simulating their exact distributions. In a similar fashion, a signs based variance ratio test is given in equation (2.23):

$$S_1 = \left(\frac{\frac{1}{Tk} \sum_{t=k+1}^{T} (S_t+S_{t-1} \ldots + S_{t-k})^2}{\frac{1}{T} \sum_{t=1}^{T} S_t^2} - 1 \right) \left(\frac{2(2k-1)(k-1)}{3kT} \right)^{-1/2} \qquad \ldots (2.23)$$

Under the null hypothesis, y_t is a martingale difference sequences whose unconditional mean is zero, S_t is an i.i.d sequence with mean zero, constant variance equal to 1, which takes the value of 1 and -1 with equal probability of ½. Thus, S_1 assumes a zero drift value. This test is also robust to many forms of conditional heteroscedasticity. Similar to R_1 and R_2, the exact sampling distribution of S_1 can easily be simulated. The test S_2 is related to the conservative test that a series is a random walk with drift[22]. The properties of S_2 are inferior to S_1 and thus it is not performed in the present study.

2.5.3 Evidences from Alternative Variance Ratio Test

The RWH is based on the premise that returns are unpredictable and it is not possible to earn abnormal profits. Rejection of random walk indicates possibility of predictable returns on past memory. The random walk hypothesis is tested using the

[22] Wright (2000) explains that S2 test first forms an exact confidence interval for the unknown nuisance parameter (the drift parameter). The underlying hypothesis series is a random walk with drift. Further, Wright (2000), explains, that by appeal to the Bonferroni inequality, this rejection rule is conservative in finite samples.

WRSVR test. Tables 2.6 and 2.7 reports test statistics, R_1, R_2 and S_1 at different *k* values namely, 2, 5, 10 and 30 for BSE and NSE respectively. The R_1 and R_2 tests are more powerful than the conventional Z_q and Z^*_q of LMVR test. The tables report only S_1 as it is shown by Wright (2000) through Monte Carlo simulation that S_1 has better power properties than S_2. Besides, Wright (2000) points that, if S_1 rejects the null, S_2 must reject as well.

It is evident from table 2.6 that with the exception of BSE Sensex, the RWH is clearly rejected by all other indices namely, BSE 100, BSE 200, BSE 500, BSE Midcap and BSE Smallcap at all *k* periods. This suggests that the stock returns are not generated by random walk process. The R_1 and S_1 test statistics for BSE Sensex at $k = 2$ and 5, and R_2 statistics at $k = 1$, are significant and thus reject the null. In other words, rejection of the null is weak as *k*-value (i.e. holding period) increases. This suggests that BSE Sensex may follows random walk at longer holding periods. It may be because of the existence of extra normal profits in short horizons which disappear in longer horizons as the information begins to reflect in current returns. Further, it can be inferred from the table that indices having lower market capitalization and liquidity such as BSE Smallcap and BSE Midcap show stronger rejection of RWH than the relatively higher market capitalized indices such as BSE 100, BSE 200 and BSE 500.

The test statistics (R_1, R_2 and S_1) for NSE are furnished in table 2.7. The results consistently support rejection of the null hypothesis for CNX Nifty Junior, CNX Defty, CNX 500, CNX IT. This indicates possibility of predictability. The evidences for CNX Nifty, CNX 100 and CNX Infrastructure are not consistent. It can be seen from the table that the R_1 and R_2 test statistics reject the null of RWH at short horizons suggesting that as

k values increase, rejection of null increasingly becomes weak. It is to be noted that the mean returns for these indices are higher than the rest. But, the S_1 statistics which are consistently significant reject the null for these (CNX Nifty and CNX 100) and thus do not support RWH. Following the rule of thumb: "reject null if there are more than two rejections at any levels of significance", RWH may be rejected for these indices[23]. Broadly, it is observed that evidences against RWH for CNX Nifty and CNX 100 for longer horizons (k = 30) are weaker than for shorter holding periods (k = 5, 10). Sector wise, non-random walk characteristics are observed in case of CNX IT for all the holding periods and similar is the case of CNX Infrastructure with the exception of R_1 and R_2 at longer holding periods where null is not rejected for CNX Infrastructure. Largely, stock returns of the indices traded at NSE exhibit non-random behaviour and thus provide space for speculation and resulting excess returns. The results for CNX Bank Nifty suggest that the stock returns do follow random walk at all holding periods as the test statistics cannot reject the null.

The behaviour of stock returns of BSE and NSE largely do not follow random walk. The results for BSE show that with the sole exception of BSE Sensex which appears to follow random walk at longer holding periods, all other indices reject RWH. Furthermore, the evidences for NSE are similar. The possible explanation for the stock returns of BSE Sensex, and also to some extent CNX Nifty and CNX 100 appear to follow random walk at longer horizons, 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 time horizon increases, information gets reflected on

[23] Hoque *et al* (2007) caution that following such rule may render the test severely over sized.

returns leading to market efficiency. 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 NSE. The results from signs test are fairly consistent but are known to be less powerful than ranks test. It may however be pertinent to note that the signs test is more powerful compared to the conventional variance ratio tests.

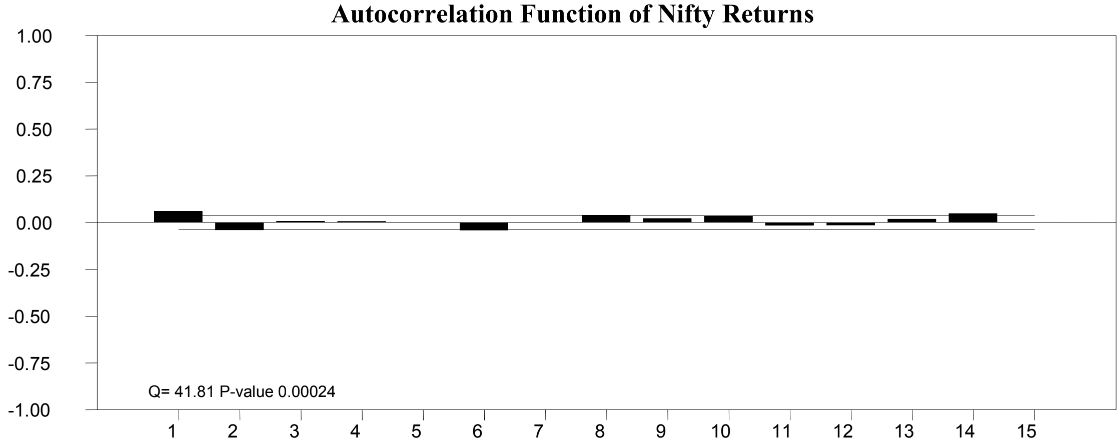
The results of the WRSVR test by and large indicate rejection of RWH for the selected indices both at NSE and BSE. However, evidences against null of random walk for BSE Sensex are weak at longer holding period. This can be attributed to existence of excess returns in short period and as information begins to reflect in returns, these profits disappear. Similar observations are made for CNX Nifty and CNX 100. Rejection of random walk is relatively stronger for smaller and medium indices than larger indices. This inference is consistent with Belaire-Franch and Opong (2005) and Hung *et al* (2009). Sector wise, inefficiency is observed in stock returns of CNX IT and CNX Infrastructure. However, CNX Bank Nifty appears to follow random walk. It may be because of the fact that the CNX Bank Index is an index comprised of the most liquid and large capitalized Indian Banking stocks and the sector is appropriately regulated by Reserve Bank of India (RBI). The results of the study are consistent with earlier studies for India as well which found that stock returns in India do not follow a random walk.

2.6 Concluding Remarks

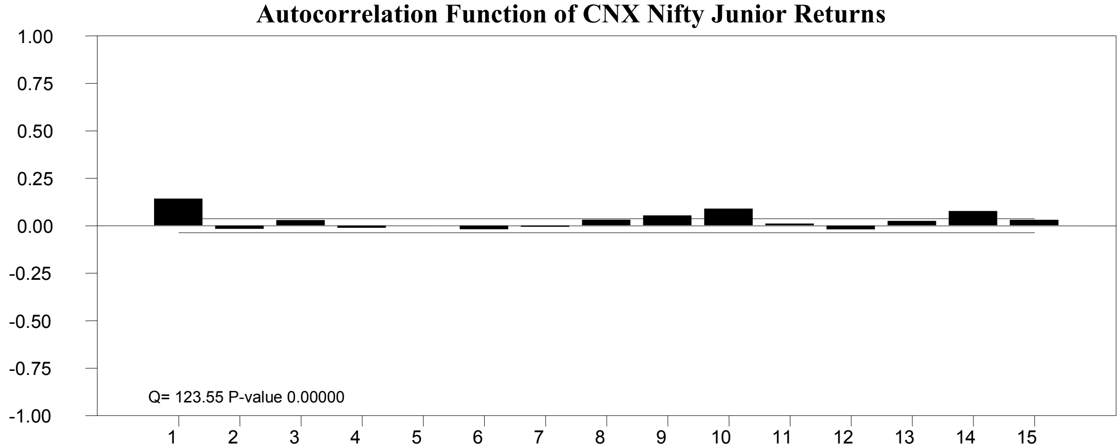
The present chapter has investigated the behaviour of stock returns by testing random walk hypothesis, in emerging Indian equity market. The major objective of the present chapter was to test weak form of market efficiency in Indian equity market. Towards this end, parametric and non-parametric tests are used to analyze the daily data on 14 market indices from two major stock exchanges namely, NSE and BSE. The results from parametric tests offered mixed results. However, parametric test results suggest non-rejection of random walk for highly liquid and considerable market capitalized indices. Sector-wise, results largely indicate random walk behaviour for selected sectoral indices. Alternative non-parametric variance ratio test employed further supports this view but only for CNX Nifty and BSE Sensex, the highly active indexes. 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 the stricter definition of random walk.

Figure 2.1: Autocorrelation Function of Index Returns

Autocorrelation Function of Nifty Returns



Autocorrelation Function of CNX Nifty Junior Returns



Autocorrelation Function of CNX Defty Returns

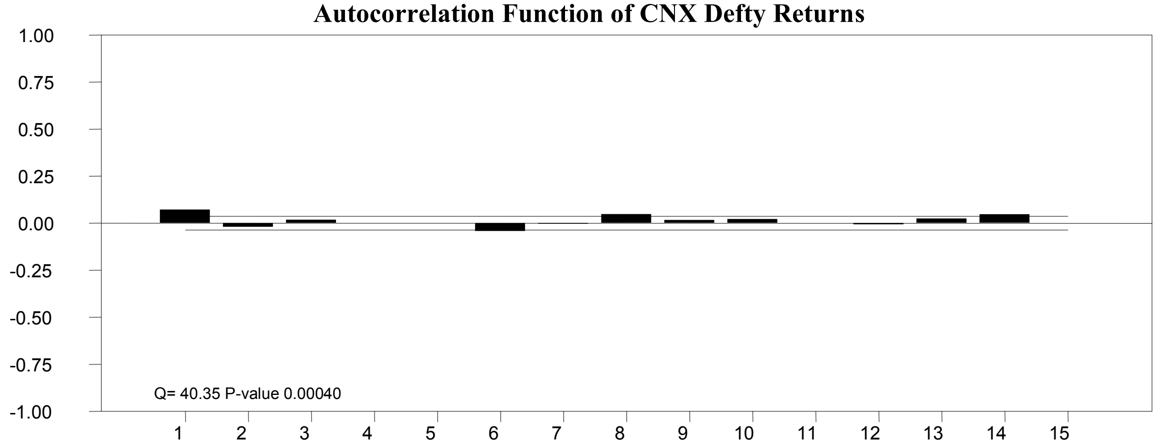
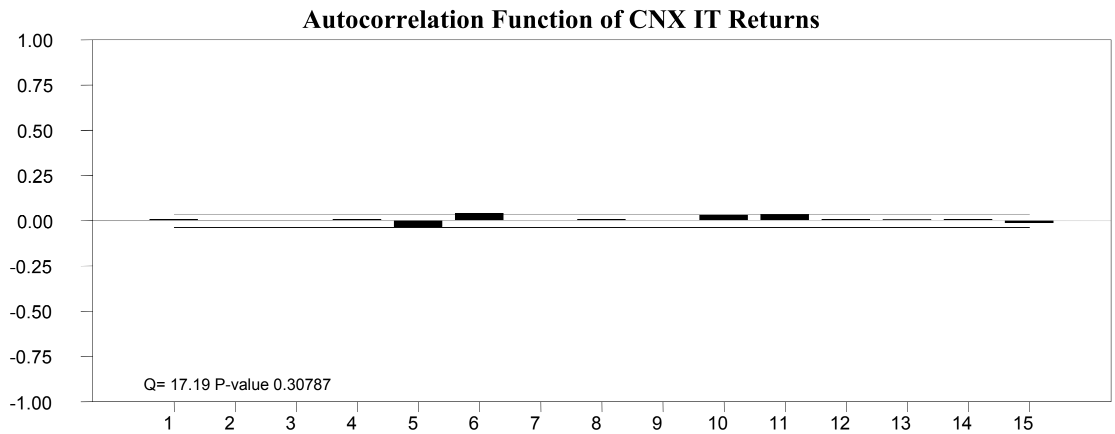
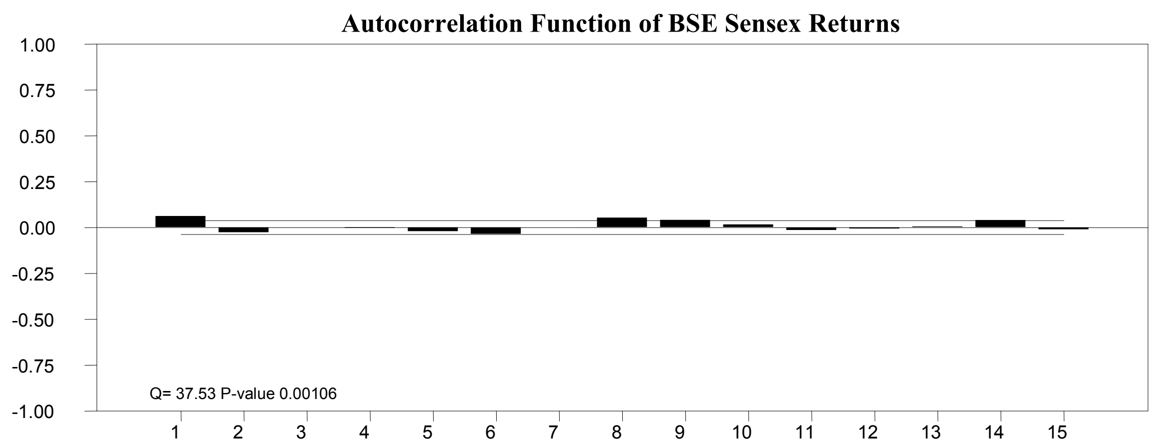


Figure 2.1: (Contd.,)





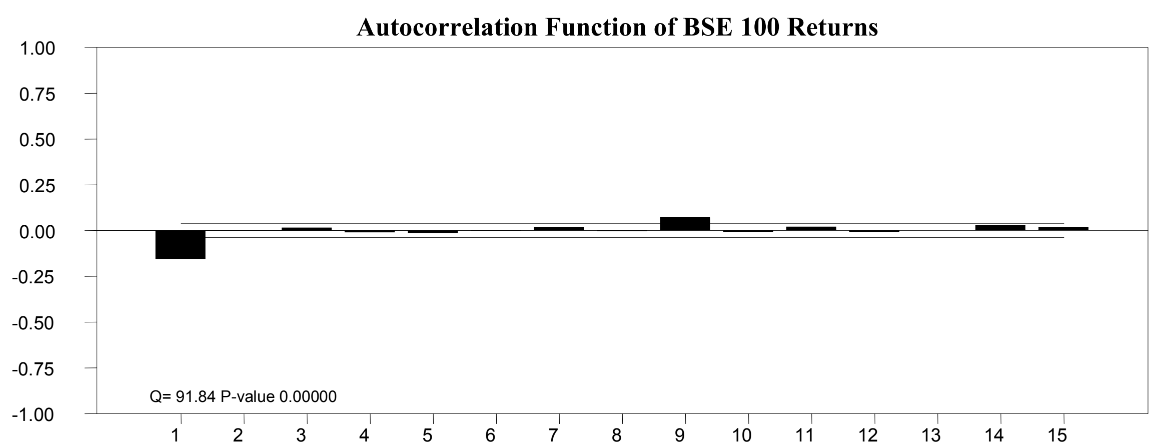
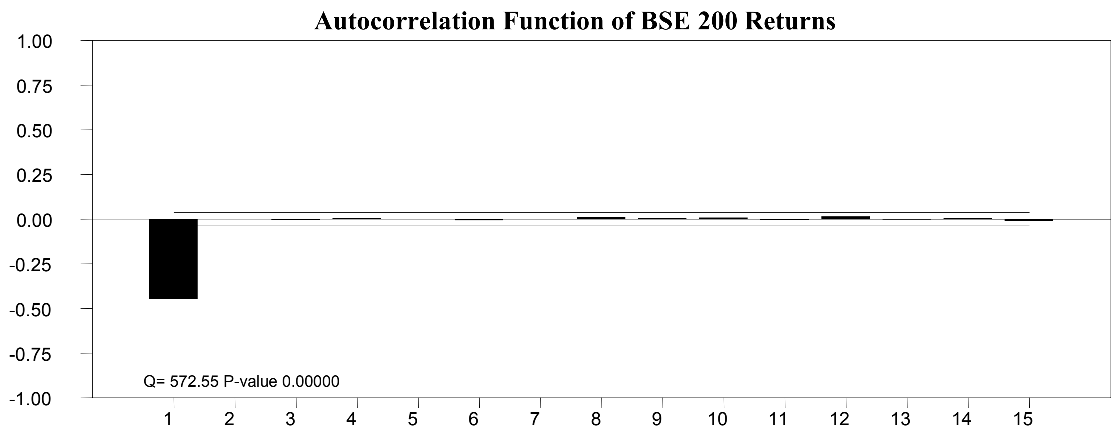
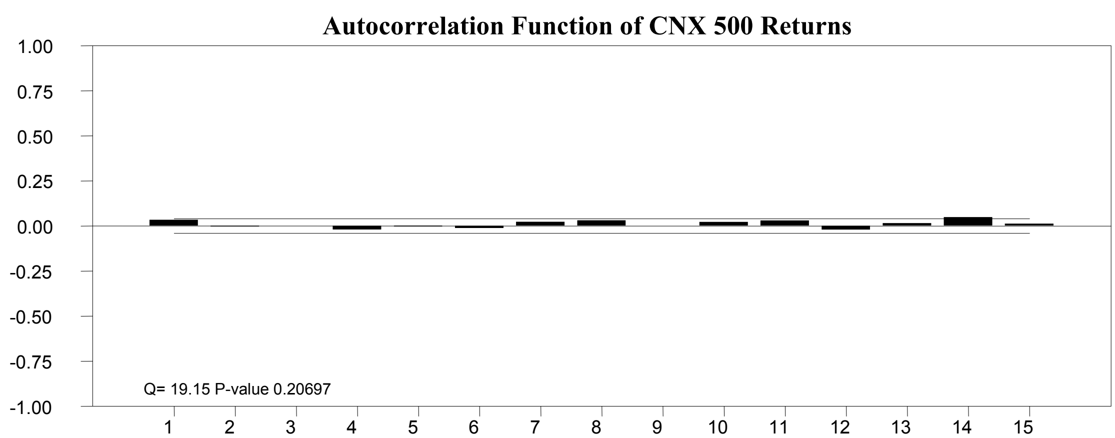


Figure 2.1: (Contd.,)





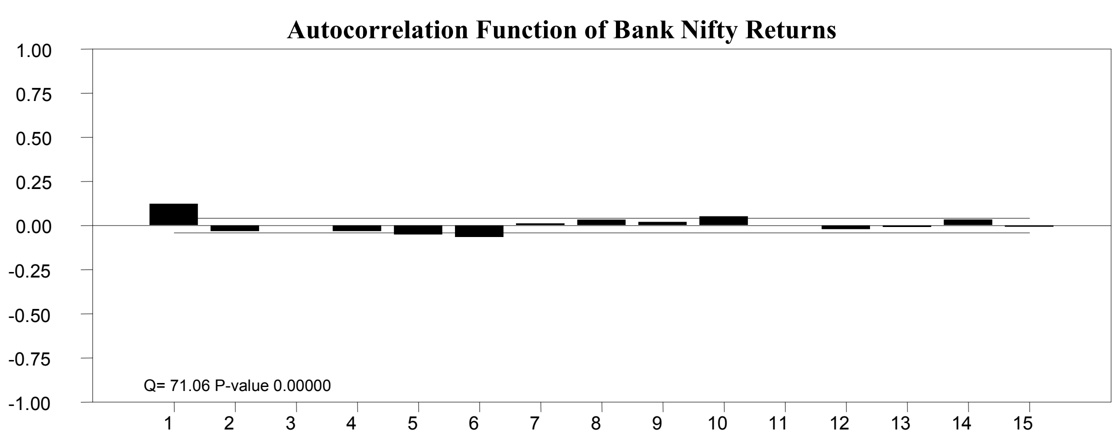
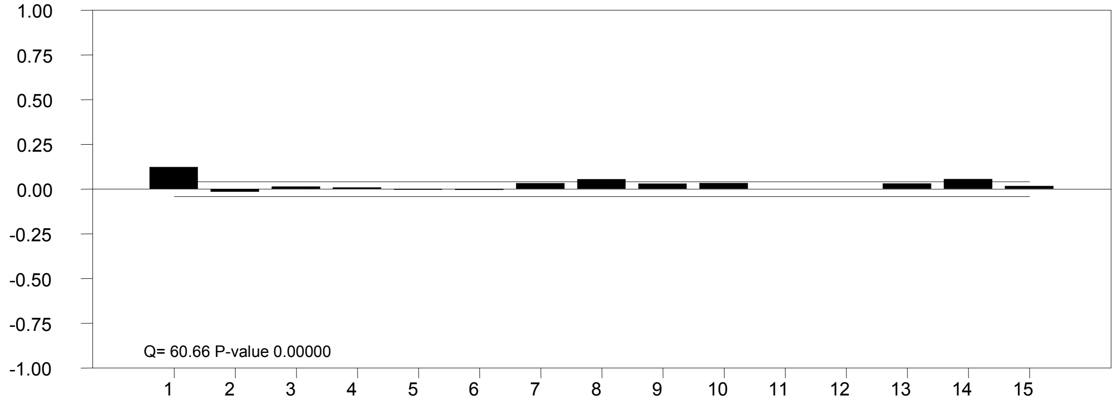
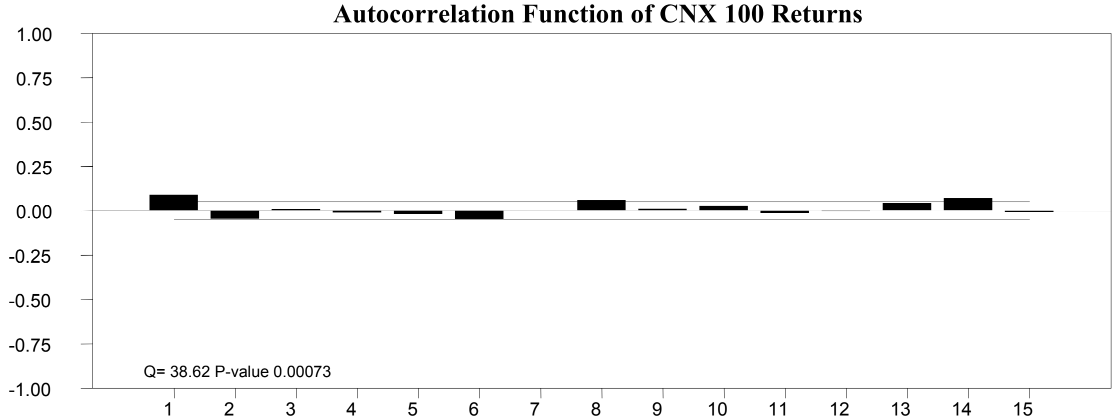


Figure 2.1: (Contd.,)

Autocorrelation Function of BSE 500 Returns



Autocorrelation Function of CNX 100 Returns



Autocorrelation Function of CNX Infrastructure Returns

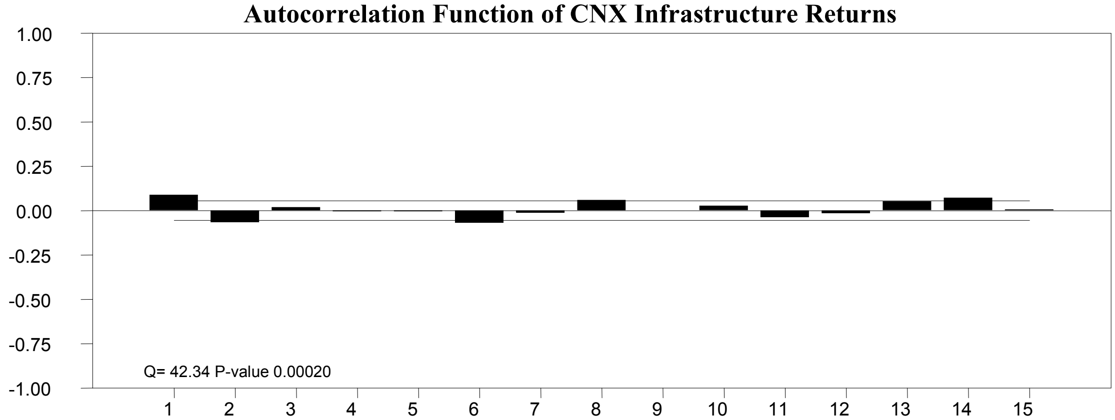
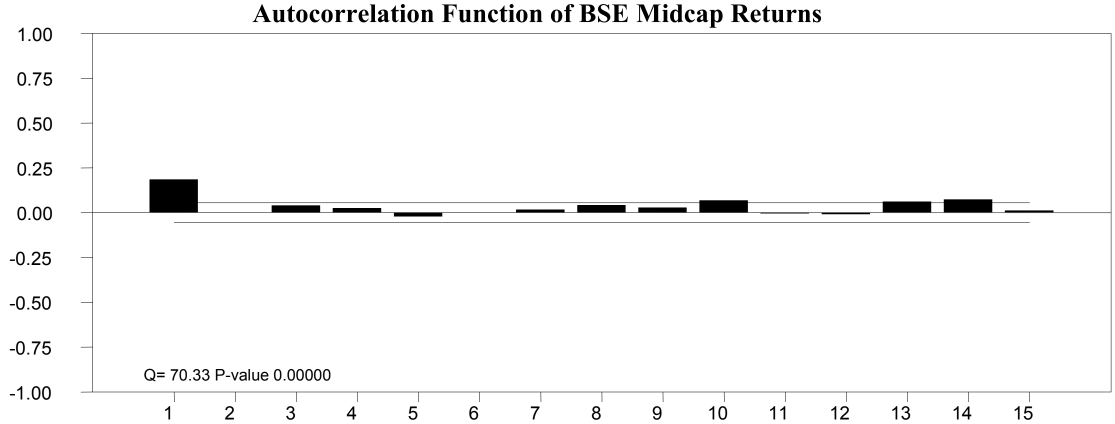


Figure 2.1: (Contd.,)

Autocorrelation Function of BSE Midcap Returns



Autocorrelation Function of BSE Smallcap Returns

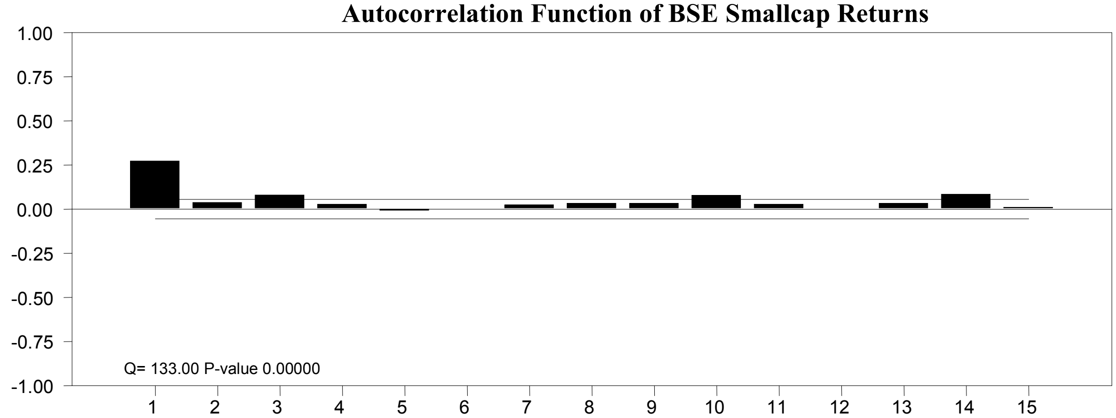


Table 2.1: Summary Statistics

Index Returns	Mean	Minimum	Maximum	Std.Dev	Skewness	Kurtosis	Jarque-Bera	P value	Q (20)
CNX Nifty	0.000352	0.07969	0.01743	0.017484	-0.51921	4.47514	2566.928	0.0000	54.3
CNX Junior	0.000458	-0.13133	0.0829	0.020527	-0.67820	3.80787	1987.318	0.0000	130.5
CNX Defty	0.000234	-0.14113	0.08985	0.018531	-0.47204	4.69874	2792.704	0.0000	50.9
CNX IT	0.000187	-2.36583	0.14556	0.051938	-32.05115	1449.94	2327.864	0.0000	18.5
BSE Sensex	0.000345	-0.15021	0.10212	0.017809	-0.39940	6.05755	2064.842	0.0000	49.8
BSE 100	0.000400	-1.47331	0.55293	0.023933	-1.47331	241.078	66926.37	0.0000	95.5
BSE 200	0.000412	-1.03708	1.08456	0.063972	-0.06899	12.487	5085.416	0.0000	574.0
CNX 500	-0.00005 2	-0.12884	0.07694	0.030893	-27.32103	4.53366	2327.864	0.0000	22.49
CNX Bank	0.000614	-0.15138	0.11401	0.021784	-0.42328	4.19325	1731.887	0.0000	81.80
BSE 500	0.000273	-0.24982	0.07532	0.018658	-1.69004	17.3739	2973.094	0.0000	75.4
CNX 100	0.000667	-0.13049	0.08006	0.018059	-0.83520	5.92625	2414.447	0.0000	22.4
CNX Infra	0.000659	-0.15021	0.10212	0.021825	-0.75894	6.05755	2064.842	0.0000	53.2
BSE Midcap	0.000144	-0.12076	0.0783	0.018377	-1.26659	7.01082	3002.329	0.0000	81.7
BSE Smallcap	0.000171	-0.10835	0.06476	0.019092	-0.87443	4.14124	1232.220	0.0000	136.9

Note: Basic statistics for 14 indices are given in the table. The null of skewness and kurtosis =0, is significantly rejected. Q (20) refers to the Ljung-Box portmanteau test statistic for up to 20^{th} order serial correlation. CNX Infra = CNX Infrastructure. Std.Dev = Standard deviation.

Table 2.2: Autocorrelations of Index Returns

Index Returns	Lags	LB Q Statistic	Q Significance
CNX Nifty	15	41.81	0.0002*
CNX Junior	15	123.55	0.0000*
CNX Defty	15	40.35	0.0004*
CNX IT	15	17.19	**0.3079**
BSE Sensex	15	37.53	0.0011*
BSE 100	15	91.84	0.0000*
BSE 200	15	57.55	0.0000*
CNX 500	15	19.15	**0.2070**
CNX Bank Nifty	15	71.06	0.0000*
BSE 500	15	60.66	0.0000*
CNX 100	15	38.62	0.0007*
CNX Infrastructure	15	42.34	0.0002*
BSE Midcap	15	70.33	0.0000*
BSE Smallcap	15	133.00	0.0000*

Note: The LB Q statistic is given in the table up to 15^{th} order autocorrelation for all series. 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. *indicates rejection of null hypothesis at 1% level of significance.

Table 2.3: Variance-Ratio and Chow Denning Statistic for Index Returns

Index Returns	Variance Ratios for Different Investment Horizons				Chow Denning
	2	4	8	16	
CNX Nifty	1.062	1.053	1.036	1.087	1.93554
	(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	4.26921*
	(7.75)*	(6.04)*	(4.22)*	(4.96)*	
	(4.26)*	(3.46)*	(2.59)*	(3.29)*	
CNX Defty	1.072	1.094	1.091	1.163	2.22679
	(3.89)*	(2.72)*	(1.66)	(2.00)*	
	(2.22)*	(1.62)	(1.04)	(1.32)	
CNX IT	1.008	1.016	1.026	1.113	0.53818
	(0.43)	(0.47)	(0.48)	(1.39)	
	(0.33)	(0.43)	(0.44)	(1.20)	
BSE Sensex	1.070	1.069	1.034	1.093	2.34265
	(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	0.76055
	(-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	0.82037
	(0.61)	(0.40)	(0.42)	(0.69)	
	(0.81)	(0.54)	(0.57)	(0.95)	
CNX 500	1.138	1.189	1.221	1.380	3.62379*
	(6.81)*	(4.98)*	(3.68)*	(4.25)*	
	(3.63)*	(2.78)*	(2.21)*	(2.75)*	
CNX Bank Nifty	1.123	1.146	1.049	1.047	3.23927*
	(5.90)*	(3.73)*	(0.80)	(0.51)	
	(3.21)*	(2.16)*	(0.50)	(0.34)	
BSE 500	1.123	1.173	1.217	1.396	3.37238*
	(5.91)*	(4.42)*	(3.50)*	(4.29)*	
	(3.39)*	(2.66)*	(2.24)*	(2.96)*	
CNX 100	1.093	1.096	1.054	1.126	1.85454
	(3.65)*	(2.01)*	(0.71)	(1.12)	
	(1.85)	(1.06)	(0.40)	(0.68)	
CNX Infrastructure	1.091	1.078	1.031	1.061	1.60863
	(3.26)*	(1.49)	(0.38)	(0.49)	
	(1.63)	(0.78)	(0.21)	(0.30)	
BSE Midcap	1.220	1.350	1.464	1.688	3.42666*
	(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	5.27285*
	(9.96)*	(9.60)*	(8.84)*	(8.65)*	
	(5.28)*	(5.42)*	(5.45)*	(5.86)*	

Note; 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 . The Chow-Denning (1993) heteroscedastic statistics, CD_2 is given in the last column. Asterisked values reject random walk hypothesis at 5% level significance.

Table 2.4: Runs Test Statistics for Index Returns

Index Returns	Actual Runs	Expected Runs	Z-statistic
CNX Nifty	1144	1258	- 4.59*
CNX Nifty Junior	1081	1183	- 4.35*
CNX Defty	1193	1253	- 2.42*
CNX IT	1183	939	11.32*
BSE Sensex	1126	1231	- 4.29*
BSE 100	1104	1231	- 6.41*
BSE 200	1079	1228	- 6.10*
CNX 500	872	993	- 5.5*
CNX Bank Nifty	1114	1259	-5.83*
BSE 500	851	982	- 5.10*
CNX 100	533	546	- 0.85
CNX Infrastructure	670	423	17.31*
BSE Midcap	557	472	4.36*
BSE Smallcap	471	219	5.28*

Note: Under null of random walk, actual runs should be equal to expected runs. * indicates test statistics is significant at 1 % level.

Table 2.5: BDS Test Statistics for Index Returns

Index Returns	m=2, ε = 0.5*S*	m=4, ε = 0.75*S*	m=6, ε = *S*	m=8, ε = 1.25*S*	m=10, ε = 1.5*S*
CNX Nifty	12.38 (0.0000)	20.45 (0.0000)	26.80 (0.0000)	31.25 (0.0000)	32.25 (0.000)
Nifty Junior	16.00 (0.0000)	24.28 (0.0000)	30.74 (0.0000)	35.60 (0.0000)	36.99 (0.0000)
CNX Defty	12.69 (0.0000)	20.31 (0.0000)	26.23 (0.0000)	30.56 (0.0000)	31.77 (0.0000)
CNX IT	19.35 (0.0000)	25.36 (0.0000)	25.64 (0.0000)	25.07 (0.0000)	24.16 (0.0000)
BSE Sensex	12.83 (0.0000)	21.42 (0.0000)	28.39 (0.0000)	33.38 (0.0000)	34.70 (0.0000)
BSE100	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)
CNX 500	14.77 (0.0000)	23.20 (0.0000)	31.01 (0.0000)	35.92 (0.0000)	36.36 (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)
BSE 500	14.58 (0.0000)	23.35 (0.0000)	30.64 (0.0000)	34.37 (0.0000)	34.05(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 Infrastructure	10.37 (0.0000)	17.67 (0.0000)	23.69 (0.0000)	26.67 (0.0000)	26.89 (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)

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 independently and identically distributed, where the alternative hypothesis assumes a variety of possible deviations from independence including non-linear dependence and chaos.

Table 2.6: Ranks and Signs Variance Ratio Tests Statistics for BSE Index Returns

Index Returns	BSE Sensex	BSE 100	BSE 200	BSE 500	BSE Midcap	BSE Smallcap
k value				R_1		
k=2	2.85*	3.73*	4.17*	5.56*	7.08*	8.17*
k=5	2.40*	4.06*	4.31*	5.60*	6.48*	8.78*
k=10	1.38	3.31*	3.66*	5.69*	4.91*	7.49*
k=30	-0.09	2.37*	2.50*	5.12*	3.09*	5.30*
				R_2		
k=2	2.06*	2.84*	3.35*	5.03*	6.73*	8.23*
k=5	1.60	2.92*	3.16*	4.37*	5.62*	8.19*
k=10	0.85	2.35*	2.66*	4.29*	3.72*	6.33*
k=30	-0.15	2.06*	2.16*	4.30*	2.12*	3.98*
				S_1		
k=2	2.54*	3.35*	3.70*	5.60*	6.88*	7.34*
k=5	2.10*	3.41*	3.89*	5.35*	7.80*	8.96*
k=10	1.21	2.75*	2.88*	4.94*	8.46*	9.57*
k=30	-0.19	1.79*	1.86*	4.73*	10.29*	12.01*

Note: Tables provides Wright's (2000) variance ratio test statistics. The test statistics for R1, R2, and S1 for *k*, holding periods 2, 5, 10 and 30 are given in panels 1, 2, and 3. '*' indicates significance at 5 % level.

Table 2.7: Ranks and Signs Variance Ratio Tests for NSE Index Returns

Index Returns	CNX Nifty	CNX NJ	CNX Defty	CNX 100	CNX 500	CNX IT	CNX Bank	CNX Infra
K value				R_1				
k=2	3.37*	4.48*	5.27*	3.13*	5.46*	5.27*	2.31*	3.95*
k=5	2.94*	4.54*	6.63*	1.42*	5.43*	6.63*	1.11	2.47*
k=10	2.11*	3.46*	5.63*	0.58	5.07*	5.63*	0.63	1.29
k=30	0.47	3.75*	5.87*	0.20	4.66*	5.87*	0.39	0.79
				R_2				
k=2	2.43*	4.21*	5.39*	2.82*	5.31*	5.39*	2.88*	3.47*
k=5	1.77*	3.67*	6.07*	0.95	4.57*	6.07*	0.98	1.64
k=10	1.26	2.81*	5.03*	0.21	4.15*	5.03*	0.09	0.43
k=30	0.26	3.65*	5.41*	-0.13	3.97*	5.41*	-0.16	0.23
				S_1				
k=2	3.18*	4.28*	2.14*	3.76*	5.55*	2.14*	0.58	3.87*
k=5	3.24*	4.67*	3.85*	3.09*	5.60*	3.85*	0.37	4.44*
k=10	2.12*	3.67*	3.29*	4.03*	5.35*	3.29*	0.48	4.22*
k=30	-0.08	3.12*	4.41*	6.22*	6.23*	4.41*	0.80	5.78*

Note: Tables provides Wright's (2000) variance ratio test statistics. The test statistics for R1, R2, and S1 for k, *holding* periods 2, 5, 10 and 30 are given in panels 1, 2, and 3. '*' indicates significance at 5 % level. CNX NJ = CNX Nifty Junior.

CHAPTER - 3

NON-LINEAR DEPENDECE IN STOCK RETURNS: SOME EVIDENCES

3.1 Introduction

Non-linear dependence in stock returns has gained importance in recent times as it indicates possibility of predictability. The earlier studies which examined the EMH largely used conventional tests such as autocorrelation, variance ratio, and runs tests which are not capable of capturing non-linear patterns in returns series. The earlier evidences of rejection of linear dependence are not sufficient to prove independence in view of non-normality of series (Hsieh, 1989). The rejection of linear dependence does not necessarily imply independence (Granger and Anderson, 1978). The presence of non-linearity provides opportunities to market participants to make excess profits. The use of linear models in such conditions may give wrong inference of unpredictability. Further, the presence of non-linearity in stock returns contradicts EMH.

Hinich and Patterson (1985) were first among others who provided evidence of non-linear dependence in NYSE stock returns. The market crash of October 1987 has shifted the paradigm. The crash is the major event which influenced the role of non-linearities in dynamics of stock returns (Lima, 1998). The stylized fact that the stock return series follows a random walk has been challenged by later studies [see e.g Fama and French, 1988, Poterba and Summers, 1988; Lo and MacKinlay, 1988] and non-linear behviour in the US exchange rate and stock market were reported [Hsieh, 1989; Scheinkman and Le Baron, 1989]. Further, Willey (1992), Lee *et al* (1993), Pagan (1996), Blasco *et al* (1997), Lima (1998), Yadav *et al* (1999) and Dahl and Nielson (2001) examined non-linear behaviour of stock returns as an alternative to random walk and found non-linearity in the underlying returns. Similar results were also reported for the UK [Newell *et al,* 1997; Abhyankar *et al,* 1995; Opong *et al,* 1999]. While examining the presence of non-linearity in Malaysian stock returns, Mahamood and Asimakopoulas (2001) observed conditional heteroscedasticity as responsible for observed non-linearity in returns. The study employed three tests namely, McLeod and Li (1983) test, Engel (1982) ARCH test and third momentum test due to (Hsieh, 1989). Solibakke (2005) distinguished between 'models that are non-linear in mean and hence depart from the martingale hypothesis and models that are non-linear in variance and hence depart from assumption of independence but not from the martingale hypothesis. In the empirical work, Solibakke (2005) found strong non-linearity in variance and weak dependence in mean of Norwegian stock returns.

It may be noted that most of the studies cited above are confined to the well developed markets. Given the fact, it is interesting to see whether stock returns exhibit the same patterns in emerging markets as well. Sewell *et al* (1993) provided evidence of non-linearity in the emerging markets. Similarly, Cinko (2002) for Turkey, Scheicher (1996) for Vienna, Afonso and Teixeira (1998) for Portugal, Seddighi and Nian (2004) for China, Panagiotidis (2005) for Greece and Dorina and Simina (2008) for 8 emerging economies (Romania, Hungary, Czech Republic, Lithuania, Poland, Slovakia, Slovenia, Turkey), and Hassan *et al* (2003) for Kuwait provided evidence of non-linearity in stock returns. Recently, Lim and Brooks (2009) who used a set of non-linearity tests reported non-linear structure in stock returns of China.

The overwhelming empirical evidence of non-linear structure in stock returns since late 1980s, both from developed and emerging economies, indicates possible predictability of future returns. However, non-linear dependence present throughout sample period or confined to a certain period within a sample period is important enough to explore. Such possibilities cannot be denied given changes in institutional arrangements and regulatory norms. Further, events occurring during a particular period might induce non-linearity in stock returns during that period and non-linear dependency might disappear later. In case underlying returns are non-linear for a few episodes, then it is difficult to make any forecast of future returns. To examine such possibilities, Hinich and Patterson (1995) suggest windowed test procedure. Under this procedure, whole sample should be divided into windows and then apply Hinich (1996) bicorrelation test.

The studies by Ammermann and Patterson (2003), Bonilla *et al* (2006), Lim (2008), Lim *et al* (2003a), Lim *et al* (2008) employed this windowed test procedure in empirical studies. Ammermann and Patterson (2003) reported brief periods of linear and non-linear dependence and disappearance of such dependencies before they could be exploited by investors. Similar episodic transient non-linear dependencies were reported by Bonilla *et al* (2006) for Latin America, Lim *et al* (2003a) for four ASEAN countries. Several of non-linear tests were performed by Lim *et al* (2008) on non-overlapping sample for the period 1992-2005 for 10 Asian emerging markets, and documented dependencies in returns. The windowed bicorrelation test, in contrast, provides evidence of non-linear dependencies only in a few periods. The other periods seem to follow pure noise process. The existence of dependency in a few periods indicates co-existence of weak form efficiency and non-random walk behaviour which is explained by market sentiments (Lim *et al,* 2003b). Strong evidence of non-linear dependence is also found in Egypt, Israel, Jordon, Morocco and South Africa and thus rejecting earlier evidences of weak form efficiency in these markets. However, bispectrum test employed could not reject null of linearity (Lim, 2009). Lim (2008**)** using bicorrelation test examined sectoral efficiency of Malaysian stock market. It was observed that the tin and mining sector were relatively more efficient compared to the property sectors which exhibited wide deviations from random walk. The study concluded that the inefficiency had been the highest during the period of Asian financial crisis. Using the same test on 50 countries, Lim and Brooks (2008) found that deviation from random walk was more persistent in low income economies. The variations might be due to low GDP and variations in property rights protection in low income countries. Conditional heteroscedasticity has been cited as one of the responsible factor for observed non-linear dependence in returns (Mahamood and Asimakopoulas, 2001; Poshakwale, 2002). Extensive application of BDS test to examine the issue of non-linearity is seen.

For India, Amanulla and Kamaiah (1998) reported independence of returns, whereas Mitra (2000), Chaudhuri and Wu (2004), Ahmad *et al* (2006)*,* concluded that stock returns in India do not follow a random walk. These studies have employed conventional tests which are not capable of detecting non-linear structure in the data. However, an exception is the study by Poshakwale (2000) which employed BDS test on a sample of 100 actively traded stocks on BSE for the period 1990-1998 to detect non-linear dependence. The study found evidence of non-linear dependence and concluded that RWH could not hold in case of 100 stocks traded on BSE.

The issue of non-linear dependence in stock returns has not been addressed in the Indian context, with the exception of the study by Poshakwale (2002). In the light of the fact that the stock market in India has witnessed several changes since the mid 1990's, the present study assumes relevance, and seeks to examine non-linear behavior of stock returns in two premier stock exchanges namely, NSE and BSE. The study relates to the period June 1997 to March 2009 and uses a wider set of data. To investigate the issue, a set of non-linearity tests is applied. Also, to examine persistence of dependence, windowed test procedure of Hinich (1995) is followed. Further, an attempt is made to identify events that occurred during the periods for which Hinich (1996) test detects significant presence of non-linear dependence.

The remainder of the chapter is organized in the following sections. Section 3.2 briefly describes methodology (non-linearity tests). Section 3.3 discusses empirical results and concluding remarks are given in the last section.

3.2. Non-linearity Tests

A set of non-linear tests namely, Hinich bispectrum (1989), McLeod and Li (1983), Tsay (1986), Brock *et al* (1996), and Hinich bicorrelation (1996) tests are employed to examine the non-linear structure in stock index returns of the NSE and the BSE. Further, to examine whether presence of non-linear dependence is pertinent during whole sample period or a few sub-periods, Hinich (1995) windowed test procedure is followed. The tests are implemented after removing linear dependence in daily returns by fitting an AR (ρ) model. A brief description of these tests is given in present section.

3.2.1 The Hinich Bispectrum Test

Hinich bispectrum test is a test of linearity and Gaussianity as described in Hinich and Patterson (1989). The Hinich bispectrum test is a frequency domain test. It estimates bispectrum of stationary time series and provides a direct test for non-linearity in returns series. The flatness of the skewness function in this frequency domain test indicates third order non-linear dependence.

3.2.2 McLeod and Li (1983) Test

The McLeod and Li (1983) portmanteau test of non-linearity seeks to test whether squared autocorrelation function of returns is non-zero.

3.2.3 Tsay (1986) Test

The Tsay (1986) test of non-linearity seeks to detect quadratic serial dependence in the data. It tests the null that all coefficients are zero.

3.2.4 BDS Test

The Brock *et al* (1996) proposed a portmanteau test (BDS test) for time based dependence in a series. It has power against a variety of possible deviations from independence including linear dependence, non-linear dependence, or chaos. In this test, m denotes the embedded dimension (period histories), and ε is a distance that is used to decide if returns are near each other. The estimate of the correlation integral value is the proportion of pairs of m period histories that are near to each other. The BDS statistic is estimated at different m, and ε values.

3.2.5 Hinich (1996) 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 for each window is that the transformed data are realizations of a stationary pure white noise process that has zero correlation (C) and bicorrelation (H). Thus, under the null hypothesis, the correlation (C) and bicorrelation (H) are expected to be equal to zero. The alternative hypothesis is that the process in window has some non-zero correlation (second order linear) or bicorrelations (third order non-linear dependence). The linear dependence in returns is removed using an AR (ρ) model. An appropriate lag is selected so that there is no significant (C) statistics. Hence, rejection of null of pure noise implies non-linear dependence. Further, the Hinich and Patterson (1995) test procedure involves dividing the full sample period into equal-length non-overlapped windows to capture episodic dependencies in stock returns. The present study divides whole sample into a set of non-overlapped window of 50 observations in equal length[24]. Then, Hinich (1996) bicorrelation test is applied to detect episodic non-linear dependencies in returns

3.3 Empirical Results

The present section presents non-linearity tests results. The non-linear dependence in stock returns is examined through applying the set of non-linear tests mentioned in the above section. Before performing these tests, linear dependence is removed by fitting AR (ρ) model so that any remaining dependence would be non-linear. The results for McLeod-Li and Tsay tests are reported in table 3.1. The former tests the null of i.i.d while the latter tests that all coefficients are zero. Rejection of null suggests that the underlying returns series are non-linearly dependent. The McLeod-Li test strongly rejects the null of i.i.d as probability values for all index returns are zero. CNX IT and CNX 500 are however exceptions to this (see table 3.1). The Tsay test results support the presence non-linear dependence as evidenced by the McLeod-Li test. Tsay test results suggest that with

[24] Hinich and Patterson (1995) suggest that the window length should be sufficiently large to validly apply bicorrelation test and yet short enough for the data generating process to have remained roughly constant.

sole exception of CNX IT, all other index returns are characterized by non-linear dependence (see table 3.1).

Further, the Hinich bispectrum tests the null of absence of third order non-linear dependence (flat skewness function). Rejection of null suggests a non-linear process. Unlike other non-linear tests, the bispectrum directly tests for linearity. Hence, filtering of data is not necessary before performing the test. In other words, the test is invariant to linear filtering. In the present study, the bispectrum though performed both on raw data and residuals, the results are reported only for raw returns as results for both the series are the same. It is evident from last column of table 3.1 that the bispectrum test rejects the null of absence of third order non-linear dependence for all the index returns.[25]

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. The BDS test statistics are furnished in table 3.2. In the table, the value in each cell represents BDS test statistic followed by probability value in parenthesis. The BDS tests the null hypothesis that returns series are i.i.d. Rejection of the null implies that random walk hypothesis does not hold good. It is clear from the statistics reported in table 3.2 that null of i.i.d is rejected for all indices. The rejection of i.i.d for residuals from AR (ρ) models indicates presence of non-linear structure in returns series. This implies possible predictability of future returns based on past information.

The Hinich (1996) bicorrelation (H) test statistics covering the full sample period are presented in table 3.3. The null of pure noise is tested. The total number of

[25] The bispectrum test could not be calculated for CNX IT, BSE 200 and CNX 500.

bicorrelations and corresponding probability values are provided in columns 2 and 3 of table 3.3. It is evident from the probability values that, with exception of CNX IT and CNX 500 as in case of McLeod-Li and Tsay tests, the null of pure noise is clearly rejected by all other index returns both from NSE and BSE. It may be inferred that returns series are characterized by non-linear dependencies as the bicorrelation test applied to residuals extracted after fitting AR (ρ) model. The null of pure noise could not be rejected for CNX IT and CNX 500, as the probability value is almost close to 1(see table 3.3).

Whether non-linear dependence presents throughout the sample period or confined to a certain sub-period within the sample is an interesting issue to explore. This helps to understand nature of market efficiency over a period of time. To examine the episodic dependence in returns series, Hinich and Patterson (1995) suggested dividing the sample into different windows and then testing the null of pure noise. To remove linear dependence from the data, an AR (ρ) model is fitted and then following Lim *et al* (2008), the residuals are divided into a set of non-overlapped window of 50 observations in equal length and then H statistics of Hinich (1996) are computed to detect non-linear dependencies in each window. The lag is selected so that there are no significant (C) windows at 5 percent probability value.

Table 3.4 presents total number of significant (H) windows in column 3, and the percentage of significant windows to total number of windows is given in column 4 of table 3.4. The results show that the number of significant (H) windows on an average is low. These significant windows reject the null of pure noise indicating presence of non-linearity confined to these windows. The BSE Midcap and BSE Smallcap index returns are characterized by highest percentage of non-linear dependence (38.4 %) followed by CNX

Nifty Junior (32.2 %) and CNX 500 (26.5 %). While the BDS test rejects the null of i.i.d for CNX IT and CNX 500, the other non-linear tests including Hinich (1996) test suggest that these two index returns validate weak form efficiency. However, it is not unsurprising that CNX IT and CNX 500 posses pockets of non-linear dependencies as is evident from table 3.4. The events occurred during these windows do not seem to influence the overall performance of CNX IT and CNX 500 index returns. This view is suggestive and not determinative.

The evidences from non-linear tests, namely McLeod-Li, Tsay, Hinich bispectrum, BDS and Hinich bicorrelation tests employed in the study provide strong evidences of non-linear dependence in both NSE and BSE across all index returns considered. The windowed Hinich test results document that the reported dependence is confined to a few brief episodes. This implies that the events during the small number of significant window periods are responsible for rejection of null of pure noise for the whole sample period. Given the fact, events occurred during these periods of significant windows provide further insight into issue of non-linearity in returns.

Theoretically, the non-linear structure in data is explained by different factors. The characteristics of market microstructure, restrictions on short sale (Antoniou *et al,* 1997), noise trading (McMillan, 2003), market imperfections (Dwyer *et al*, 1996; Anderson and Vahid, 2001), heterogeneous beliefs (Sarantis, 2001) are factors cited in literature, responsible for non-linear dependency structure in stock returns. In the context of heterogeneous behaviour of investors, Lim and Hinich (2005), and Lim *et al* (2006), examined whether non-linear burst associated with major economic and political events. Instead of hypothesizing prior event as in case of event study methodology, Lim and

Hinich (2005), and Lim *et al* (2006) proposes an alternative approach where the non-linear dependency is first detected through Hinich (1996) bicorrelation with windowed procedure and identifying major events occurred during the significant window period which exhibited non-linear dependency. Following the framework, attempt is made here to identify those events which probably induced non-linear dependency in those window periods which are found to be significant by Hinich (1996) test.

The period of significant windows of respective indices are given in the last column of table 3.4. The major political and economic events occurred during the year January 1997 to March 2009 are identified. These events are associated with those periods of significant windows reported in table 3.4 based on Hinich (1996) test with windowed procedure. The major events are identified through news reports and events cited as important by various issues of annual reports of RBI and SEBI. These are discussed in the Appendix at the end of this chapter.

The different indices reacted to different events differently. One possible reason may be due to different market capitalization and liquidity. For instance, BSE Midcap and BSE Smallcap immediately responded to crisis and they are more vulnerable. Both positive and negative events are found to be associated with existence of non-linearity. However, negative events have greater and persistence impact. The sub-prime crisis, uncertainties in international oil prices, global financial crisis have impact on a longer period and it was for almost all indices. The presence of non-linearity confounds EMH in Indian equity market.

3.4 Concluding Remarks

The issue of non-linear dependence though gained importance in recent time, is seldom discussed in India. Motivated by this concern, the present chapter attempted to test non-linear dependence in stock returns of indices at two premier Indian stock exchanges namely, NSE and BSE. A set of non-linear tests are applied to examine the behavior of stock returns. Strong evidences of non-linear dependences for almost all index returns of NSE and BSE are found in the study. The results from windowed Hinich test showed that the reported non-linear dependencies are not consistent during the whole period suggesting presence of episodic non-linear dependencies in returns series surrounded by long periods of pure noise. The events occurred during the episodes of presence of non-linearity are identified. Both positive and negative events though identified, but negative events have larger impact. The major events identified are uncertainties in international oil prices, turbulent world markets, sub-prime crisis, global economic meltdown and political uncertainties importantly border tensions. The investigation into intraday and tick-by-tick data would provide further insights regarding existence of non-linearity and associated events. The presence of non-linear structure in returns data during 1997-2009 is consistent with earlier findings of Poshakwale (2002) for BSE.

Table 3.1: McLeod-Li, Tsay and Bispectrum Test Statistics

Index Returns	Mc Leod-Li Test Statistics (probability)	Tsay Test Statistic Lag 4	Tsay Test Statistic Lag 6	Bispectrum Test Statistic
CNX Nifty	0.0000	6.25 (0.0000)	4.41 (0.0000)	3.75 (0.0000)
Nifty Junior	0.0000	6.97 (0.0000)	4.16 (0.0000)	13.03 (0.0000)
CNX Defty	0.0000	6.97 (0.0000)	4.81 (0.0000)	16.64 (0.0000)
CNX IT	1.0000	1.12 (0.3414)	13.60(0.000)	-
BSE Sensex	0.0000	5.76 (0.0000)	3.73 (0.0000)	7.00 (0.000)
BSE100	0.0000	75.11 (0.0000)	36.66 (0.000)	31.26 (0.0000)
BSE 200	0.0000	91.83 (0.0000)	44.04 (0.000)	-
CNX 500	1.0000	2.42 (0.0070)	1.71 (0.0219)	-
CNX Bank Nifty	0.0000	4.05 (0.0000)	2.99 (0.0000)	13.36 (0.0000)
BSE 500	0.0000	5.72 (0.0000)	3.80 (0.0000)	18.08 (0.0000)
CNX 100	0.0000	6.53 (0.0000)	4.58 (0.0000)	17.88 (0.0000)
CNX Infrastructure	0.0000	5.89 (0.0000)	4.56 (0.0000)	20.3 (0.0000)
BSE Midcap	0.0000	8.17 (0.0000)	4.59 (0.0000)	30.26 (0.0000)
BSE Smallcap	0.0000	6.37 (0.0000)	3.70 (0.0000)	10.19 (0.0000)

Note: The McLeod-Li statistics tests the null hypothesis that the increments are independently and identically distributed, and the corresponding p values are given in second column. Tsay statistics tests that all coefficients are zero. Alternative hypothesis is that returns series are characterized by non-linear dependence. Tsay statistics is calculated at lag 4 and 6 and respective statistic followed by p values in parentheses is given. The bispectrum statistics test the null of absence of third order non-linear dependence. The bispectrum statistic is given in last column along with p values in parentheses. The bispectrum test could not be calculated for CNX IT, BSE 200 and CNX 500.

Table 3.2: BDS Test Statistics

Index Returns	m=2, ε = 0.75s	m=4, ε = 1.0s	m=8, ε =1.25 *S*	m=10, ε=1.50s
CNX Nifty	12.94 (0.0000)	20.53 (0.0000)	31.25 (0.0000)	32.07 (0.0000)
Nifty Junior	15.81 (0.0000)	23.77 (0.0000)	35.49 (0.0000)	37.08 (0.0000)
CNX Defty	13.15 (0.0000)	20.56 (0.0000)	31.04 (0.0000)	32.18 (0.0000)
CNX IT	19.32 (0.0000)	23.39 (0.0000)	25.53 (0.0000)	24.60 (0.0000)
BSE Sensex	13.71 (0.0000)	22.00 (0.0000)	34.67 (0.0000)	35.94 (0.0000)
BSE100	18.99 (0.0000)	25.78 (0.0000)	32.72 (0.0000)	31.41 (0.0000)
BSE 200	28.16 (0.0000)	27.04 (0.0000)	21.87 (0.0000)	18.91 (0.0000)
CNX 500	16.89 (0.0000)	21.78 (0.0000)	23.97 (0.0000)	22.08 (0.0000)
CNX Bank Nifty	12.37 (0.0000)	17.75 (0.0000)	24.94 (0.0000)	25.81 (0.0000)
BSE 500	15.03 (0.0000)	23.10 (0.0000)	34.02 (0.0000)	33.57 (0.0000)
CNX 100	11.98 (0.0000)	18.26 (0.0000)	28.44 (0.0000)	28.63 (0.0000)
CNX Infrastructure	10.27 (0.0000)	16.93 (0.0000)	26.21 (0.0000)	26.13 (0.0000)
BSE Midcap	11.96 (0.0000)	16.63 (0.0000)	22.94 (0.0000)	22.16 (0.0000)
BSE Smallcap	10.20 (0.0000)	13.68 (0.0000)	18.63 (0.0000)	19.12 (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 (0.75, 1, 1.25 and 1.5) of standard deviation (*s)* of the data. The value in the first row of each cell is 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 independently and identically distributed, where the alternative hypothesis assumes a variety of possible deviations from independence including non-linear dependence.

Table 3.3: Hinich Bicorrelation (H) Statistics for Full Sample

Index Returns	Number of Lags	Number of Bicorrelations	Probability (p) Value for (H) Statistic
CNX Nifty	24	276	0.0000*
CNX Nifty Junior	24	276	0.0000*
CNX Defty	24	276	0.0000*
CNX IT	24	276	**1.0000**
BSE Sensex	23	253	0.0000*
BSE 100	23	253	0.0000*
BSE 200	23	253	0.00008
CNX 500	23	231	**0.9999**
CNX Bank Nifty	22	231	0.0000*
BSE 500	22	231	0.0000*
CNX 100	18	153	0.0000*
CNX Infrastructure	17	136	0.0000*
BSE Mid Cap	17	136	0.0000*
BSE Small Cap	17	136	0.00008

Note: The table reports Hinich bicorrelation test statistics. Under the null of pure noise, the bicorrelations are expected to be zero. Rejection of null hypothesis suggests presence of non-linear dependence. * indicates rejection of null hypothesis of zero bicorrelation at 1 % level of significance.

Table 3.4: Windowed Test Results of Hinich H Statistic

Index Returns	Total Number of Windows	Total Number of Significant H Windows	Percentage of Significant Windows	Windows Period
CNX Nifty	59	10	16.9	01/12/98 – 03/26/98, 06/10/98 – 08/18/98, 01/04/01 – 03/19/01, 08/09/01 – 10/22/01, 10/24/02 – 01/06/03, 03/16/04 – 05/26/04, 12/28/04 – 03/10/05, 03/09/06 – 05/23/06, 12/22/06 – 03/08/07, 12/26/07 – 03/04/08.
CNX Nifty Junior	59	19	32.2	08/16/99 – 10/25/99, 01/01/00 – 03/16/00, 03/21/00 – 06/01/00, 10/25/00 – 01/03/01, 08/09/01 – 10/22/01, 10/23/01 – 01/07/02, 03/19/02 – 05/30/02, 05/31/02 – 08/08/02, 06/03/03 – 08/11/03, 01/01/04 – 03/15/04, 03/16/04 – 05/26/04, 12/28/04 – 03/09/05, 05/23/05 - 08/01/05, 03/09/06 – 05/23/06, 05/24/06 – 07/31/06, 10/12/06 – 12/21/06, 12/26/07 – 03/04/08, 08/01/08 – 10/15/08, 10/16/08 – 01/01/09.
CNX Defty	59	10	16.9	06/02/97 – 08/11/97, 08/10/00 – 10/19/01, 10/23/02 – 01/03/03, 03/17/04 – 05/27/04, 12/29/04 – 03/10/05, 03/10/06 – 05/24/06, 05/25/06 – 08/01/06, 10/13/06 – 12/22/06, 12/26/06 – 03/09/07, 12/27/07 – 03/05/08.

CNX IT	59	9	15.2	10/24/97 – 01/07/98 01/08/98 – 03/24/98, 11/05/99 – 01/17/00, 03/31/00 – 06/13/00, 01/16/01 – 03/28/01, 03/29/01 –06/11/01, 08/23/01 – 11/02/01, 01/10/07 – 03/23/07, 06/09/0/ - 08/18/08, 08/19/08 – 10/31/08,
BSE Sensex	56	8	14.2	10/29/98 - 01/08/99, 10/30/02 – 01/10/03, 10/28/03 – 01/06/04, 03/22/04 – 06/01/04, 12/30/05 – 03/14/06, 03/16/06 – 05/29/06, 05/30/07 – 08/07/07, 10/19/07 – 12/31/07.
BSE 100	55	13	23.6	06/04/98 – 08/12/98, 03/26/99 – 06/08/99, 01/10/01 – 03/22/01, 08/16/01 – 10/29/01, 10/30/02 – 01/10/03, 03/22/04 – 06/02/04, 01/03/05 – 03/15/05, 10/19/05 – 12/29/05, 03/16/06 – 05/29/06, 03/15/07 – 05/29/07, 01/01/08 – 03/11/08, 03/12/08 – 05/28/08, 08/07/08 – 10/22/08, 10/23/08 – 01/06/09.
BSE 200	55	12	21.8	01/01/98 - 03/18/98, 03/19/98 – 06/04/98, 06/05/98 – 08/12/98, 01/10/01 – 03/22/01, 08/16/01 – 10/29/01, 10/30/02 – 01/10/03, 03/22/04 – 06/01/04, 01/03/05 – 03/15/05, 03/16/06 – 05/29/06, 05/30/06 – 08/04/06,

				10/18/06 – 12/28/06, 03/15/07 – 05/29/07, 01/01/08 – 03/11/08, 03/12/08 – 05/28/08, 08/07/0/ - 10/21/08, 10/22/08 – 01/06/09.
CNX 500	49	13	26.5	10/26/99 – 01/05/00, 01/04/01 – 03/16/01, 08/09/01 – 10/22/01, 10/24/02 – 01/06/03, 06/03/03 – 08/11/03, 03/19/04 – 05/31/04, 12/31/04 – 03/14/05, 10/18/05 – 12/28/05, 03/14/06 – 05/26/06, 05/29/06 – 08/03/06, 05/29/07 – 08/06/07, 12/31/07 – 03/10/03, 08/06/08 – 10/20/08.
CNX Bank Nifty	45	7	15.5	10/19/00 – 12/28/00, 08/03/01 – 10/16/01, 05/27/02 – 08/02/02, 03/10/04 – 05/20/04, 12/22/04 – 03/03/05, 10/09/07 – 12/17/07, 12/18/07 – 02/27/08
BSE 500	47	8	17.0	03/14/00 – 05/29/00, 01/01/01 – 03/13/01, 08/06/01 – 10/17/01, 10/21/02 – 01/01/03, 03/11/04 – 05/21/04, 12/23/04 – 03/04/05, 10/09/06 – 12/18/06, 12/19/07 – 02/28/08.
CNX 100	31	7	22.5	05/28/03 – 08/05/03, 03/10/04 – 05/20/04, 12/22/04 – 03/03/05, 10/06/05 – 12/20/05, 03/06/06 – 05/18/06, 12/19/06 – 03/06/07, 02/29/08 – 05/16/08.

CNX Infrastructure	31	7	22.5	05/27/04 - 08/05/04, 03/10/05 – 05/23/05, 12/26/05 – 03/09/06, 10/12/06 – 12/21/06, 03/09/07 – 05/23/07, 12/26/07 – 03/04/08, 01/01/09 – 03/18/09
BSE Midcap	26	10	38.4	12/28/04 – 03/09/05, 05/23/05 – 07/29/05, 08/01/05 – 10/11/05, 10/13/05 – 12/23/05, 03/09/06 – 05/23/06, 05/24/06 - 07/31/06, 12/22/06 – 03/08/07, 12/24/07 – 03/04/08, 08/01/08 – 10/15/08, 10/16/08 – 12/31/08.
BSE Smallcap	26	10		01/01/04 – 03/15/04, 03/16/04 – 05/26/04, 12/28/04 – 03/09/05, 08/01/05 – 10/11/05, 03/09/06 – 05/23/06, 05/24/06 – 07/31/06, 10/12/06 – 12/21/06, 12/26/07 – 03/04/08, 08/01/08 – 10/15/08, 10/16/08 – 12/31/08.

Note: Total number of significant H windows and the percentage to total number of windows is furnished in the table. A window is significant if the H statistic rejects the null hypothesis at a 5 % probability value. Last column of the table presents significant window dates.

Appendix

1997-1998

The financial year 1997-98 witnessed a higher level of volatility. The market-friendly budget of 1997-98 had favourable impact as there was spurt in stock returns up to middle of August. The significant window period for CNX IT falls in October '97 to January'98 (see table 3.4). This period was associated with events such as currency crisis in South East Asia which generated panic in the market resulting in negative net Foreign Institutional Investors (FIIs) inflows.

1998-99

The performance of market in general was gloomy during the year. The significant windows period during this financial year are associated with the events such as impending sanctions following nuclear test, instability in exchange rate and turmoil in international market and the bad news of US-64 scheme of UTI scam.

1999-00

The massive inflow of FIIs and mutual funds in both NSE and BSE created upward pressure in stock returns during the months August'99 – October'99 and late October'99 – February'00. The new Government was formed at the Centre. The new government passed several reform bills[26] and RBI in its annual report pointed that the market positively responded to the news of rating India as stable market by international credit rating agencies. However, the uncertainty about international oil price and hike in interest rate by US Fed, dot.com bubble burst on March 10, 2000 and on political front, the hijack of Air

[26] The bills passed during the year were Insurance Regulatory Authority (IRA) Bill, Foreign Exchange Management Act (FEMA) Securities Laws (Amendment) Bill.

India followed by war hysteria between India and Pakistan during January'00 – March'00 generated nervousness in the market. Annual report of SEBI reported that behaviour of stock returns was not linear during the year.

2000-01

The significant windows indicating non-linearity in the financial year 2000-01 were for the months March-June, October-December and January'00 – March'00 (see table 3.4). The events such as increase in international oil prices and, panic in international equity market are associated with these periods. Generally, the Indian equity market witnessed sharp decline in all indices during the year 2000-01. The last quarter of the year, January'00-March'00 witnessed high volatility. The RBI's annual report 2000-01 indicated the Union budget, expectations of strong earnings, growth of new economy as responsible factors for sharp rise. Besides, the fall was due to liquidity /solvency of some co-operative banks.

2001-02

During the year especially August-October'01, bearish sentiment prevailed in the market. The US stock market crashed following terrorist attack on World Trade Centre on September 11, 2001. The slowdown in major international stock market aggravated depression and resulted in heavy selling by FIIs in Indian stock market.

2002-03

The events associated with the period identified as period of significant windows (see table 3.4) were India-Pakistan border tension, slip in consumer spending and bad monsoon, tension in Middle East and rise in international oil prices. The Bank Nifty responded to new information of profitability of banks and relaxation of Foreign Direct Investment (FDI) norms for private sector banks.

2003-04

The Indian equity market witnessed 83 per cent returns which are highest in any emerging markets. The RBI annual report of the year pointed that the improved fundamentals, strong corporate results and initiatives on disinvestment and active derivative trading were responsible for the spurt in returns. SEBI allowed brokers to extend margin trading facility. The period of January-March'04 was period of political uncertainties leading to depression in market.

2004-05

The turbulent political conditions of March'04 continued up to May'04 and resulted in lackluster in returns. The major indices such as BSE Sensex reached lowest on May 17, 2004 due to political uncertainties. These uncertainties made the market nervous. During the period May – July – August and October – December'04, due to strong economic outlook, high and sustained portfolio investment, market responded quickly and rally of returns continued.

2005-06

The first quarter of the financial year March'04/April – May'05 was marked by prevalence of bearish sentiment in the market and associated events during the period were uncertainty relating to the global crude oil prices, rise in interest rates and turmoil in international stock markets. The corrections during the period October – December'05 were because of response of market to the news of rise in domestic inflation rate, uncertainty regarding crude oil prices. The proposals of Union Budget 2006-07 including raising FIIs investment limit and improving fundamentals, sound business outlook were met by rally in stock returns during the last quarter, January'-Marhc'06.

2006-07

The period of significant windows during the financial year March'05 – May'06 were associated with the sharp fall in metal prices, uncertainty in global interest rate and inflationary pressure in the economy. Hike in Cash Reserve Ratio (CRR) and Bank rate by RBI are associated with significant window period, October-December'06. The impending recession in US and deterioration in sub-prime mortgage banking in US adversely affected the Indian equity market.

2007-08

The financial year 2007-08 was highly volatile as BSE crossed 20,000 mark and in the same year reached lowest ever in Indian equity market. The first and second quarter (continued with corrections) witnessed buoyant trend (May-August'07). The disarray because of US sub-prime crisis, surge in international oil prices, political uncertainties, policy cap on external commercial borrowings (ECBs) generated panic during October-December'07 though sharp increases were also observed (This period was highly volatile). The period of December'07 – March'08 associated with decline in developed equity markets following sub-prime crisis, global recession, fear of credit squeeze and hike in short term capital gains tax, increase in domestic inflation rate etc.

The year 2008 was year of financial crisis and global economic meltdown. The periods of significant windows during this financial year fell in March'07-May'08, June-August-October'08 and October'08 to January'09. As RBI noted in its annual report, the turbulence in global financial market began deepening in July 2008. Fannie Mac and Freddie Mac reported drop in fair value assets. On September 15, 2008, major US investment bank, Lehman Brother declared bankrupt while Merill Lynch, another major investment bank in US saved by merger with Bank of America. During January 08, Northern Rock bank crisis aggravated and JP Morgan and Citibank profits dived deep. The situation was further aggravated by Satyam scam.

CHAPTER - 4

MEAN REVERTING TENDENCY IN STOCK RETURNS

4.1 Introduction

Two extreme views are popular in the literature in respect of stock return behaviour. One view is that returns are generated by a random walk process so that it is not possible to predict their future movements based on past information. This is formally stated as RWH. The other view is the mean-reversion view, according to which there exists a tendency for the stock returns to return to its trend path. Hence, it is possible to predict future price movements based on history of prices.

The earlier studies supported the stylized fact that stock return series follows a random walk. However, this was challenged by many later studies which documented mean-reverting tendency in stock returns [Fama and French, 1988; Poterba and Summers, 1988; Lo and MacKinlay, 1988; Richards, 1995, 1997; Balvers *et al,* 2000]. Some later studies [Richardson and Stock, 1989; Kim *et al* 1991[27] ; McQueen, 1992; Richardson, 1993,) also reported evidences against mean-reversion.

The conventional view of rejection of unit root in the return series is that the current shocks have only temporary effect and the long-term series would remain unaffected by such shocks. But, Nelson and Plosser (1982) pointed that the random shocks have permanent effect on the underlying series. Empirical studies have employed largely conventional unit root tests to examine the mean-reversion issue. However, in the presence of a structural break, power of a unit root test decreases when stationary

[27] Kim *et al* (1991) pointed that mean reversion is a pre-war (World War II) phenomena.

alternative is true (Perron 1989). Thus, inference concerning mean-reversion employing conventional unit root tests is likely to go wrong when structural break is ignored. An appropriate way would be to test for the presence of structural break while employing such tests. In this context, an alternative test was proposed by Perron (1989) where break points are known before hand. Perron (1989) included dummy variables to account for one known or exogenous structural break in the framework of Dickey-Fuller (1979) unit root test. The test allows for a break under the null and alternative hypothesis. Perron (1989) proposed three models namely, Model A which allows break in mean, Model B which allows for break in slope, and Model C which allows for break both in mean and slope. He treated Great Depression and Oil shock of 1973 solely as exogenous events which altered the long run movement of stock prices. Perron (1989) provided evidence of mean-reversion for 10 of the 13 series of Nelson and Plosser (1982). A limitation of this test is that it requires knowledge of break point before hand which is more often difficult to ascertain and also involves subjectivity in the determination of break points.

To overcome this limitation, Christiano (1992), Banerjee *et al* (1992), Zivot and Andrews (1992), Lumsdaine and Papell (1997) among others proposed test procedure based on different methods. Zivot and Andrews (1992) test is most popular test employed extensively in empirical studies. Zivot-Andrews developed a sequential test procedure which endogenously searches for a break point and tests for presence of unit root when the process has a broken trend. The test selects the break date where t-statistics testing the null of unit root is minimum (most negative). They provided evidence in support of findings of Nelson and Plosser (1982) as they reject null of unit root for 3 out 13 series.

Further, Wu (1997), Chaudhuri and Wu (2003), Narayan and Smyth (2005), and Chancharat and Valadkhani (2007) studied the issue of mean-reversion and structural break using Zivot test. Wu (1997) employed the test on a sample of 11 OECD countries during the period 1979-1994. While the conventional unit root test namely, augmented Dickey and Fuller (1979) (ADF) supported the null of unit root (except for Finland and the UK), the Zivot test showed that 8 out of 11 countries were characterized by trend-stationary. Further, using monthly data from 1985-1997 for 17 emerging countries including India, Chaudhuri and Wu (2003) found evidences of mean-reversion in 10 out of 17 emerging markets. In contrast to evidences from emerging countries, the OECD countries documented evidences against mean-reversion and supported unit root process of underlying stock prices (Narayan and Smith, 2005). Chancharast and Valadkhani (2007) who used data from 7 developed and 9 emerging markets found with the exception of Malaysia and Russia, that all the countries rejected mean-reversion hypothesis. In their study of 17 emerging markets, Chaudhuri and Wu (2003) rejected null of unit root for India. The break occurred during 1991 and the authors pointed that rupee devaluation and economic reforms of 1991 were responsible for the structural break.

As mentioned earlier, Perron (1989) pointed out that ignoring a structural break may lead to loss of power of a unit root test. Similarly, ignoring multiple structural breaks (more than one) may also lead to loss of power of a test. Motivated by this concern, Lumsdaine and Papell (1997) (LP) proposed two breaks unit root test where they extended the endogenous break methodology of Zivot-Andrews test to allow for two breaks under the alternative hypothesis of unit root test[28]. The endogenous break tests such as Zivot-

[28] Clemente *et al,*(1998), Ohara (1999) , Papell and Prodan (2003) also introduced multiple break tests.

Andrews (single break) and LP (two breaks) tests do not assume break(s) under unit root null and derive their critical values. This may potentially biases tests and leads to size distortions and incorrect inferences (Nunes *et al,* 1997; Lee and Strazicich, 2003).

The single break test such as Zivot-Andrews sequential break and LP multiple breaks test assume no breaks under null of unit root. Hence, rejection of null does not necessarily imply trend stationary process. In other words, rejection of null in case of Zivot-Andrews or LP test implies rejection of unit root without breaks. Based on test statistics of these tests, one may infer that rejection of null is nothing but alternative trend stationary. However, this results in erroneous understanding of difference stationary as trend stationary. Because, since these test assumes no breaks under null of unit root, rejection of null in the presence of breaks under null in fact is difference stationary alternative as showed by Lee and Strazicich (2003, 2004). Given the fact, Lagrange multiplier (LM) unit root multiple breaks test developed by Lee-Strazicich incorporates breaks both under null and alternative. Therefore, rejection of null clearly indicates trend stationary process. Empirically, Lee-Strazicich showed potential for over rejection using LP test. Galip (2005), Cook (2005), Bruggemann and Trenkler (2005) employed Lee-Strazicich test on macroeconomic series, while Hooi and Smyth (2005), Paynes *et al* (2005) applied the same test to examine the issue of structural break in exchange rates of different countries. Narayan and Smyth (2007) using Lee-Strazicich test found evidences against mean-reversion in 6 out of 7 stock returns of G7 countries.

With the exception of the study by Chaudhuri and Wu (2003), the issue of mean-reversion of stock returns has been examined in India using conventional unit root tests only. These tests are known to be less powerful in the presence of structural breaks.

Therefore, it is more appropriate to examine the mean-reversion issue in the Indian context by employing structural break unit root tests such as Zivot and Andrews (1992) and Lee and Strazicich (2003). Accordingly, the objective of present chapter is set to re-examine the issue of mean-reversion and structural breaks in two premier Indian stock exchanges namely, NSE and BSE. Since several structural changes took place during the past decade such as establishment of the NSE, second generation reforms and seesaw changes in market microstructure among others, the present study assumes relevance. The study relates to the period January 1997 to March 2009 and uses 14 indices from the NSE and the BSE, to throw more light on this issue. The study is first of its kind which examines multiple structural breaks in Indian context. The rest of the chapter is organized as follows: Section - 4.2 describes the methodology and empirical evidences for India are presented in Section – 4.3. Concluding remarks are given in last section.

4.2 Methodology

Zivot-Andrew (1992) sequential trend break and Lee-Strazicich (2003) LM unit root (with two structural breaks) tests are employed to examine the issue of mean-reversion as alternative to RWH and structural breaks. A brief description of the same is presented in this section[29].

4.2.1 Zivot- Andrews (1992) Sequential Break Test

Zivot-Andrews developed three models namely, model A which allows for a break in intercept only, model B that allows for a break in trend only, and model C which allows for a break each in both intercept and trend. Heeding the suggestion of Sen (2003a) the

[29] The conventional unit root tests namely, ADF and Phillips-Perron (1988) are also employed for the purpose of comparison. These tests are widely discussed in literature. Therefore, these tests are not discussed here

present study employs model C to examine structural break in the data. Sen (2003b) also demonstrated through Monte Carlo simulation that model C yields more reliable breakpoints than model A when the break is unknown. Model C is given in the following equation:

$$\Delta P_t = \mu + \theta\, DU_t(\lambda) + \beta\, t + y\, DT_t(\bar{\lambda}) + \alpha\, p_{t-1} + \sum_{j=1}^{k} \phi_j\, \Delta p_{t-j} + \epsilon_t \qquad \text{. . . (4.1a)}$$

In equation (4.1a), ΔP_t is the first difference of the process P_t, DU_t is a dummy variable that captures shift in the intercept, and DT_t another dummy that represents a shift in the trend occurring at time T_B. μ, θ, β, γ, ∝ and ϕs are constants, λ is location of the break point and ε_t is the shock. These dummy variables are defined as follows:

$$DU_t(\lambda) = \begin{cases} 1 & \text{if } t > TB \\ 0 & \text{otherwise} \end{cases}$$

$$DT_t(\lambda) = \begin{cases} 1 & \text{if } t > TB \\ 0 & \text{otherwise} \end{cases} \qquad \text{. . . (4.1b)}$$

Zivot-Andrews tests the null that trend (return) variable contains a unit root with drift that excludes any structural break against the alternative hypothesis of trend-stationary process with a one-time break in the trend variable. The model allows for a one-time break both in intercept and trend. The test allows testing for a unit root against the alternative of stationarity with structural change at some unknown point. To determine the break point and compute the test statistics for a unit root, an ordinary least square regression is run with a break at T_B, where T_B ranges from 1 to T-2. For each value of T_B, the number of extra regressors k, is chosen following a sequential downward t-test on all lags as suggested by Campbell and Perron (1991). Ng and Perron (1995) showed that general-to-specific approach provides test statistics which have better properties than information based criteria[30].

4.2.2 Lee-Strazicich (2003) LM Unit Root Test with Two Structural Breaks

Let the data generating process $\{y_t\}$ be given by

$$\{y_t\} = \delta' Z_t + e, \quad e_t = \beta e_{t-1} + \varepsilon_t \qquad \text{. . . (4.2)}$$

where Z_t is a vector of exogenous variables, e_t is a vector of (first order autocorrelated) errors, δ' is a vector of parameters, β is a constant, and ε_t is an error term with zero mean and constant variance. Lee-Strazicich by extending the LM unit root test of Schmidt and Phillips (1992), developed two models namely, model AA which allows for two shifts in intercept only, and model CC that allows for two shifts each in both intercept and trend. In the present study, model CC is employed which is as follows: Let

$$\mathrm{Z_t} = [1, t, \mathrm{D}_{1t}, \mathrm{D}_{2t}, \mathrm{DT}_{1t}, \mathrm{DT}_{2t},] \qquad \text{. . . (4.3a)}$$

where Z_t is a vector of variables, t is time trend, D_{jt} and DT_{jt} (j = 1, 2) are dummy variables defined as follows:

$$D_{jt} = \begin{cases} 1 \text{for } t > TB_j. + 1 \\ 0 \text{ otherwise, and} \end{cases}$$

[30] The sequential procedure suggests first to start with $k_{\max}$ and then estimate the model with $k_{\max}$ lags. If the coefficient of the last included lag is significant at the 10 per cent level, select $k=k_{max}$. Otherwise, reduce the lag order by one until the coefficient of the last included lag becomes significant. For details see, Campbell and Perron (1991).

$$DT_{jt} = \begin{cases} 1 \text{ for } t > TB_{j}. + 1 \\ 0 \text{ otherwise,} \end{cases} \quad \text{. . . (4.3b)}$$

In the equation (4.3b), T_{Bj} is the time period when a break occurs. For model CC, the following null ($\beta = 1$) and alternative ($\beta < 1$) hypothesis in which the process y_t includes two trend breaks each in intercept and slope, may be formulated as follows:

$$\text{Null} : y_t = \mu^{(N)} + d_{11}^{(N)} B_{1t} + d_{12}^{(N)} B_{2t} + d_{21}^{(N)} BT_{it} + d_{22}^{(N)} BT_{2t} + y_{t-1} + \nu_{1t} \quad \text{... (4.4a)}$$

$$\text{Alternative: } y_t = \mu^{(A)} + d_{11}^{(A)} + D_{1t} + d_{12}^{(A)} D_{2t} + d_{21}^{(A)} DT_{1t} + d_{22}^{(A)} DT_{2t} + \nu_{2t} \quad \text{... (4.4b)}$$

In equation (4.4a) and (4.4b), the superscripts N and A denote null and alternative respectively, ν_{1t} and ν_{2t} are stationary error terms, and B_{jt} and BT_{jt} are defined as follows:

$$B_{jt} = \begin{cases} 1 \text{ for } t > TB_{j}. + 1 \\ 0 \text{ otherwise} \end{cases}$$

$$BT_{jt} = \begin{cases} 1 \text{ for } t > TB_{j.} + 1 \\ 0 \text{ otherwise} \end{cases} \quad \text{. . . (4.4c)}$$

Under the null hypothesis, it is assumed that

$$d_{11}^{(N)} = d_{12}^{(N)} = 0$$

$$d_{21}^{(N)} = d_{22}^{(N)} = 0$$

The two breaks LM unit root test statistic is obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \bar{S}_{t-1} + \mu_t \qquad ...(4.5)$$

where $\bar{S}_t = y_t - \widehat{\psi}_x - Z_t \widehat{\delta}_t,\ t = 2, \dots, T$; $\hat{\delta}$ are coefficients in the regression of Δy_t on ΔZ_t; $\widehat{\psi}_x$ is given by $y - Z\hat{\delta}$; and y and Z represent the first observations of y_t and Z_t respectively. The unit root null is described by $\phi = 0$, and the LM test statistics are given by $\hat{\rho} = T\widehat{\phi}$ and $\bar{\tau}$ = t-statistic for testing the unit root null hypothesis that $\phi = 0$. The location of the structural break (T_B) is determined by selecting all possible break points for the minimum t-statistics given by:

$$\inf_{\lambda} \hat{\rho}(\lambda) = \inf_{\lambda} \hat{\tau}(\lambda) \qquad ...(4.6)$$

The search is carried out over the trimming region of 0.10T, where T is the sample size. As in case of Zivot test, the numbers of lagged augmentation terms are determined by the general-to-specific procedure as suggested in Ng and Perron (1995). Starting from a maximum of k = 8, lagged terms, the procedure looks for significance of the last augmented term.

4.3 Empirical Evidences for India

To examine the issue of mean-reversion and for comparison purpose, conventional unit root tests namely, ADF and PP unit root tests are applied and corresponding test statistics are reported in table 4.1. These two tests have the null hypothesis of unit root (random walk) against an alternative hypothesis of stationary process. These two tests are applied with and without deterministic trend variable in levels to test null of unit root against stationary alternative. The maximum lag length is set to 12 for ADF and 4 for PP following sequential procedure. To take care of possible serial correlation in error terms, the ADF test adds lagged difference terms of the regressand in error terms, while PP test uses non-parametric methods.

The ADF and PP test statistics are furnished in table 4.1 Rejection of null without trend implies that returns series is stationary with a nonzero mean, whereas rejection of null with trend indicates that returns series is stationary around a deterministic trend. It is evident from the table that the ADF test rejects unit root hypothesis for all index returns at 1per cent level both with trend and without trend. Similarly, PP unit root test statistics presented in table 4.1 strongly support the evidences of ADF test. The unit root null is strongly rejected for all index returns at 1per cent level of significance. It may be inferred from these two tests that index returns in India are mean-reverting.

As noted earlier, the conventional unit root tests (such as ADF and PP as presented above) give spurious results if the presence of structural breaks is ignored. Hence, it is vital to see whether there is a unit root in the returns process while simultaneously taking into account possible structural break. Considering this, Zivot-Andrews sequential break (model C) test which searches for a break endogenously, is employed and results are reported in table 4.2. The general-to-specific procedure is followed to choose extra k regressors. Further, fraction of data range to skip at either end while examining possible break is fixed as 0.15T (trimming region). Table 4.2 shows that Zivot-Andrews test provides no evidence against mean-reversion. In other words, the results are not significantly different from those reported in table 4.1.

The plot of stock returns for 14 indices along with breaks (generated by Zivot-Andrews) is depicted in figure 4.1. The structural break points for all indices identified by Zivot-Andrews test are significant as it is evident from the minimum t-statistics on vertical axis corresponding break point of each index as shown in figure 4.1. Further, the structural break for CNX IT and BSE 100 in the year 2000 is associated with global economic slowdown and dot-com internet bubble burst. The structural break for CNX Nifty, BSE Sensex, BSE 200, and BSE 500 occurred in 2003, the period, which witnessed rise in international oil prices. The break points for CNX Bank Nifty and CNX Defty coincides with unprecedented slide of rupee in 2006. For CNX 100, CNX 500, and relatively less liquid and having lower market capitalization indices namely, CNX Infrastructure, BSE Midcap and BSE Smallcap structural break point associated with global economic meltdown of 2008 precipitated by sub-prime crisis of 2007 in the US.

It may be pertinent to note that ignoring a structural break may leads to biases and loss of power of unit root test. In the same fashion, ignoring more than one break, results in similar reduction of power of the test. Motivated by this concern, the present study applied Lee-Strazicich two structural break tests. The model CC of the Lee-Strazicich test is employed which allows for two shifts in mean and slope. The test has advantage over Zivot-Andrews and LP multiple breaks test since it includes breaks both under null and alternative hypothesis. Table 4.3 provides the Lee-Strazicich test statistics along with breaks dates. It is clearly evident from the table that out of 14 indices, 12 indices reject the null of unit root at 1 percent as indicated by significant minimum t-statistics and thus unambiguously implying trend stationary process with the exception of CNX Nifty Junior and CNX IT. In other words, the evidences are in support of mean-reversion tendency in stock returns in NSE and BSE. However, CNX Nifty Junior and CNX IT which were breakpoint stationary according to Zivot-Andrews test, do not reject the null of unit root indicating random walk behaivour.

The break dates identified by Zivot-Andrews and Lee-Strazicich, (though strictly not comparable) suggest different break points. While structural break points identified by Zivot-Andrews test for BSE 100, CNX Bank Nifty and BSE 500 are identical to first break point of Lee-Strazicich test, and for indices namely, CNX Defty, CNX 500, CNX 100, CNX Infrastructure, BSE Midcap and BSE Smallcap are identical to second break point identified by Lee-Strazicich test. The break points for rest of the indices (CNX Nifty, CNX Nifty Junior, BSE Sensex, BSE 200) are entirely different. This indicates the importance of considering two structural breaks, as single break test ignores the other structural break which is important and such ignorance leads to wrong inferences.

Lee-Strazicich test results show that the break points identified for various indices are different. Most of the break dates seem to have occurred during 2000-03 and 2006-08. The first break point for CNX Nifty, BSE Sensex, BSE 100, BSE, 200, CNX 500 falls in between 1999 and 2000. This was a period of global economic recession originated in the US, dot-com internet bubble burst and Air India hijack followed by war hysteria between India and Pakistan. It may also be noted that in March 2000, the government notified to remove the ban on future trading to pave way for derivative trading in India.

The sluggishness in FIIs, slip in consumer spending and bad monsoon during 2003 made the market to move in a narrow range. This is the year when the first break point for CNX Defty, BSE 100, BSE 500, CNX 100, occurred. The rise in international oil prices during March-May, 2003 is one of the possible factors for the break in these indices. The first structural break for BSE Midcap and BSE Smallcap which occurred in 2007 is associated with notorious sub-prime mortgage crisis broke out and collapse of many investments banks in a short span of time and there was sustained pull out of FIIs investment from Indian markets.

The second structural break point identified by Lee-Strazicich test for BSE 100 and BSE 500 falls between 2003-2004 which coincides with bad monsoons and international oil shock. There was sustained pull out of FIIs from the market and unprecedented slide of rupee in 2006. The second break point for CNX Defty and BSE Sensex occurred during this year. The second break occurred in case of most indices such as CNX Nifty, BSE 200, CNX Bank Nifty, CNX 100, CNX Infrastructure, BSE Midcap and BSE Smallcap during 2008. This is the period of global meltdown triggered by sub-prime crisis which spread to the whole financial sector and resulted in economic crisis. The BSE Midcap, BSE Smallcap, CNX Infrastructure, CNX Bank Nifty were more vulnerable to financial crisis and market meltdown as they have low capitalization and less liquid stocks than other indices.

Two structural breaks are preferable to single structural break since ignoring the second break might lead to spurious results. Further, Lee-Strazicich test is preferable to other multiple break tests such as LP test, as the former includes breaks both under null and alternative hypothesis and therefore rejection of null clearly indicates trend-stationary process. The results of the present study indicated trend stationary process in stock returns of NSE and BSE

4.4 Concluding Remarks

The present chapter re-examined the issue of mean-reversion and structural break in NSE and BSE. The conventional unit root test namely, ADF and PP, and structural break tests namely, Zivot and Andrew (1992) sequential break test, and Lee and Strazicich (2003) are employed on a sample of 14 indices of NSE and BSE between 1997 and 2009. The conventional unit root tests find evidences against random walk process. Zivot and Andrews (1992) test corroborates the mean-reverting tendency as the test strongly rejects null of unit root for all indices. The Lee and Strazicich (2003) LM unit root test further supports the mean-reversion tendency, which takes into account two endogenously determined structural breaks. This suggests that shocks possibly trigged by structural or policy change may have only a temporary impact on stock returns and there is tendency for the returns to return to trend path. The breaks occurred that are identified in 2000, 2003, 2007 and 2008 are associated with structural reforms, global economic recession, sub-prime crisis and economic meltdown. The study also suggests that the less liquid indices are more vulnerable to external shocks.

Table 4.1: ADF and PP Test Statistics

Index Returns	ADF		PP	
	Without Trend	With Trend	Without Trend	With Trend
CNX Nifty	-14.57*	-14.56*	-51.11*	-51.11*
CNX Nifty Junior	-13.40*	-13.41*	-47.05*	-47.06*
CNX Defty	-14.25*	-14.25*	-50.59*	-50.59*
CNX IT	-13.76*	-13.86*	-53.88*	-53.94*
BSE Sensex	-9.72*	-9.85*	-49.71*	-49.71*
BSE 100	-14.13*	-14.12*	-62.20*	-62.20*
BSE 200	-14.39*	-14.39*	-104.34*	-104.34*
CNX 500	-10.17*	-10.33*	-47.89*	-47.94*
CNX Bank Nifty	-12.95*	-13.04*	-42.43*	-42.44*
BSE 500	-15.20*	-15.21*	-42.43*	-42.43*
CNX 100	-13.76*	-13.86*	-36.00*	-36.08*
CNX Infrastructure	-13.33*	-13.34*	-33.08*	-33.14*
BSE Midcap	-15.20*	-15.21*	-29.96*	-30.05*
BSE Smallcap	-11.67*	-11.67*	-27.38*	-27.49*

Note: The table reports ADF and PP test statistics for model with trend and without trend. In the case of both ADF and PP tests, the critical values are 1% = -3.43, 5% = -2.86 and 10% = -2.56 for model without trend, and 1%= -3.97, 5% = -3.41, 10% = -3.13 for model with trend. * denotes significance at 1%. ADF and PP tests examine the null hypothesis of a unit root against the stationary alternative.

Table 4.2: Zivot and Andrews Sequential Trend Break Test Statistics

Index Returns	Trend Break	*k*	Minimum T Statistics
CNX Nifty	2003:04:25	7	-19.286*
CNX Nifty Junior	2003:03:31	2	-29.698*
CNX Defty	2006:06:14	7	-19.038*
CNX IT	2000:02:21	5	-22.037*
BSE Sensex	2003:05:12	7	-18.674*
BSE 100	2000:02:21	0	-62.221*
BSE 200	2003:04:29	6	-27.186*
CNX 500	2007:08:23	0	-48.288*
CNX Bank Nifty	2006:07:19	5	-22.125*
BSE 500	2003:04:01	1	-33.143*
CNX 100	2008:01:09	5	-17.652*
CNX Infrastructure	2008:01:09	5	-16.647*
BSE Midcap	2008:01:08	2	-19.528*
BSE Smallcap	2008:01:08	2	-18.169*

Note: The table reports Zivot-Andrews test statistics for model C which allows for break both in intercept and trend. The *k* is the number of extra regressors chosen following general-to-specific method. The critical values are -5.57 and -.508 for 1% and 5% respectively. * denotes statistical significance at 1 % level.

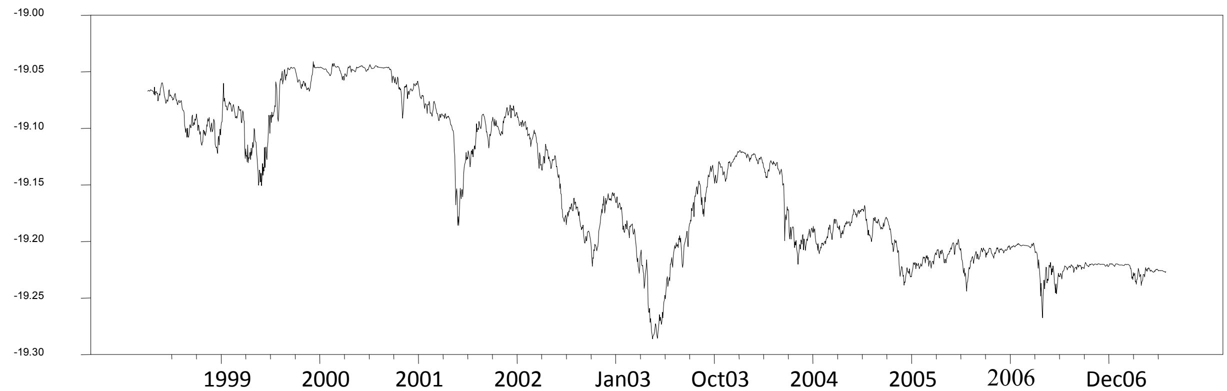
Table 4.3: Lee and Strazicich LM Unit Root Two Structural Break Test Statistics

Index Returns	Trend Break 1	Trend Break 2	Lag	Minimum T Statistics
CNX Nifty	March, 1999	January, 2008	5	-10.849*
CNX Nifty Junior	March, 2000	February, 2002	8	2.547
CNX Defty	October, 2003	July, 2006	7	-14.159*
CNX IT	May, 2004	June, 2006	4	-2.768
BSE Sensex	March, 2000	July, 2006	7	-10.629*
BSE 100	February, 2000	September, 2003	8	-9.518*
BSE 200	December, 1999	January, 2008	3	-8.417*
CNX 500	July, 2001	September, 2007	0	-9.533*
CNX Bank Nifty	July, 2006	January, 2008	5	-22.030*
BSE 500	May, 2003	June, 2004	1	-23.248*
CNX 100	October, 2003	January, 2008	5	-6.336**
CNX Infrastructure	June, 2006	January, 08	5	-17.026*
BSE Mid Cap	August, 2007	July, 2008	0	-16.053*
BSE Small Cap	August, 2007	March, 2008	2	-13.241*

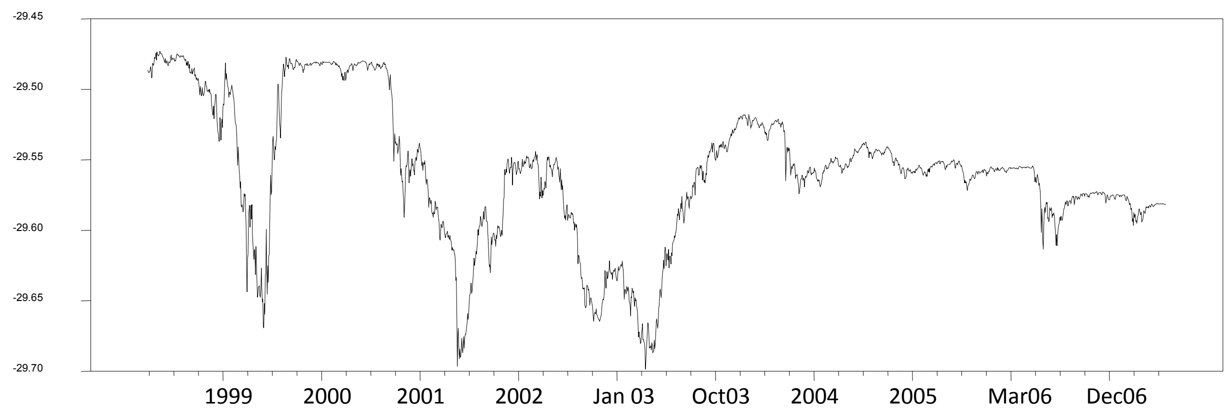
Note: Table reports Lee-Strazicich test for model C which allow two breaks each in mean and trend. The test examines the null hypothesis of a unit root with breaks against the trend stationary with breaks as an alternative. The *k* is the number of extra regressors chosen following general-to-specific method. The critical values of the test for model C are -6.281, -5.620 and -5.247 at the 1 %, 5% and 10 % significance level respectively. * indicates significance at 1 % level.

Figure 4.1: Plot of Return Indices with Structural Break

Zivot-Andrews Unit Root Tests for Nifty Returns



Zivot-Andrews Unit Root Tests for CNX Nifty Junior Returns



Zivot-Andrews Unit Root Tests for CNX Defty Returns

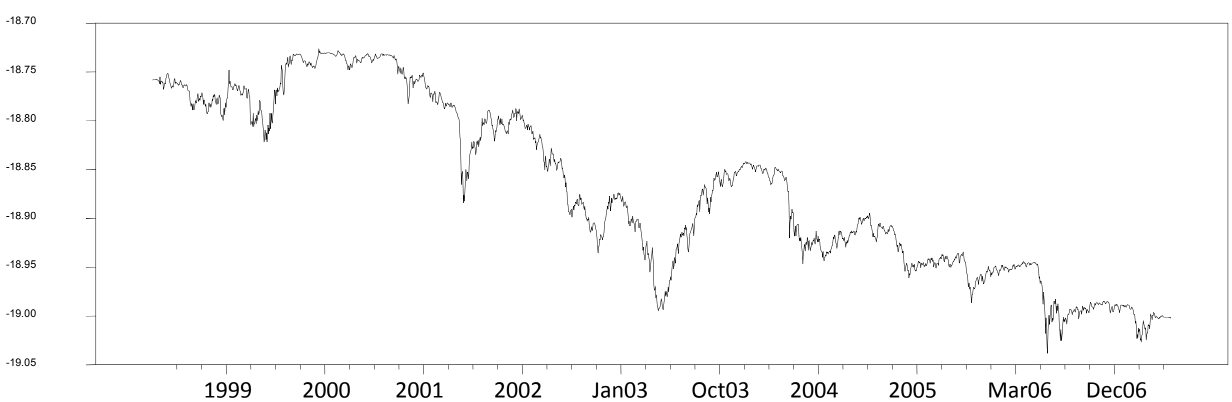
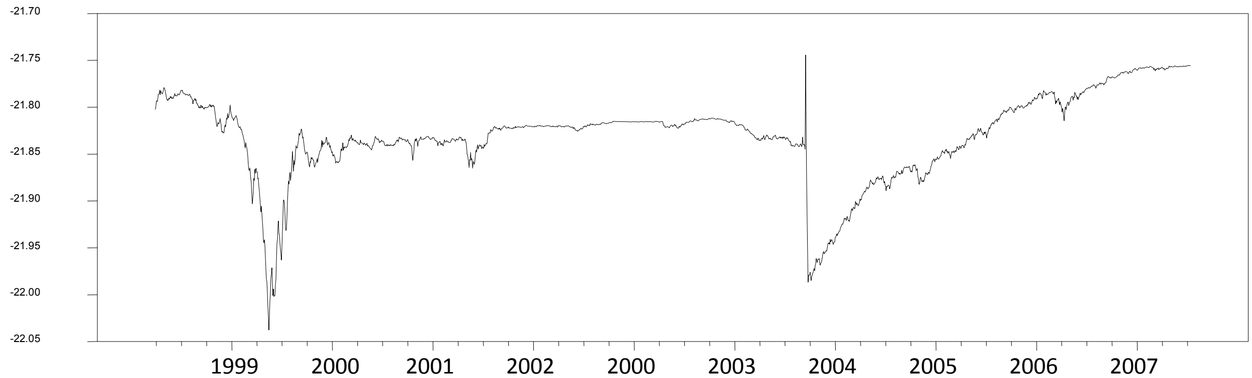
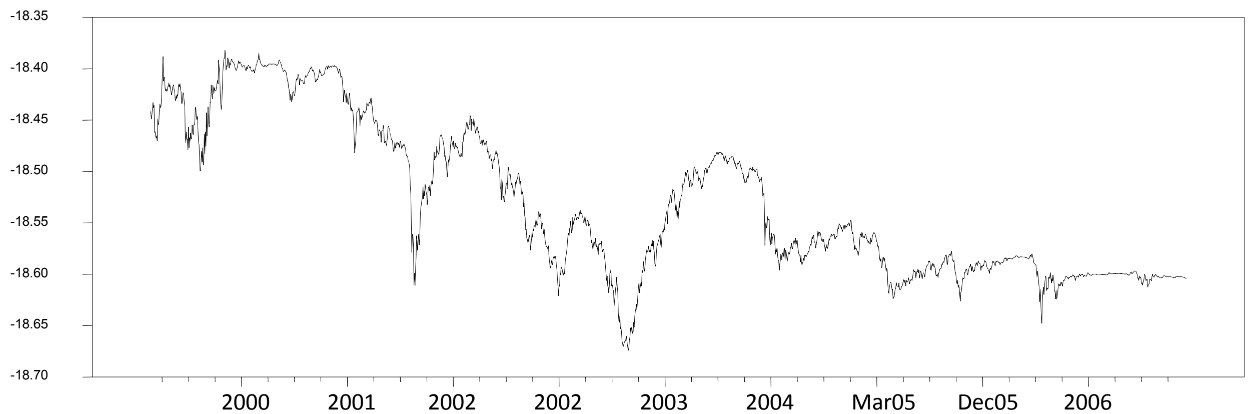


Figure 4.1: (Contd.,)

Zivot-Andrews Unit Root Tests for CNX IT Returns



Zivot-Andrews Unit Root Tests for BSE Sensex Returns



Zivot-Andrews Unit Root Tests for BSE 100 Returns

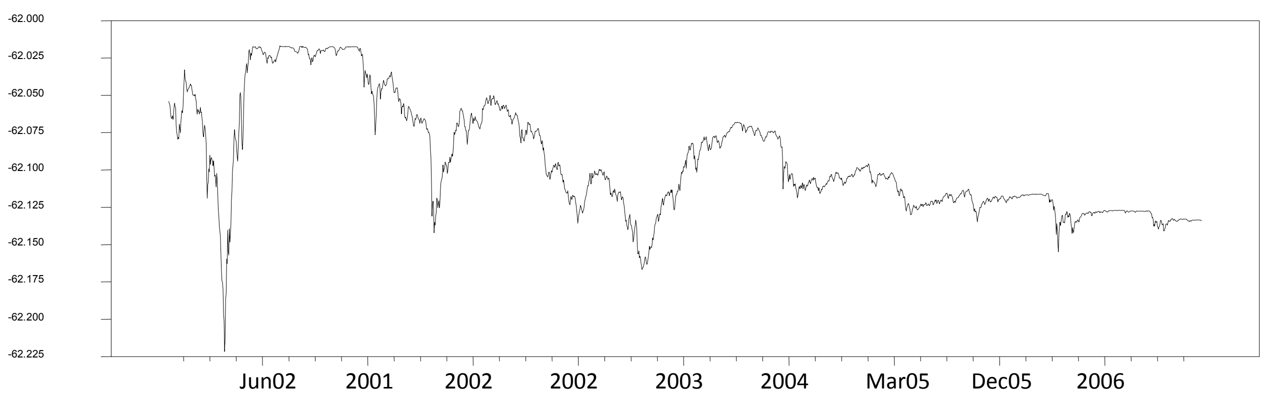
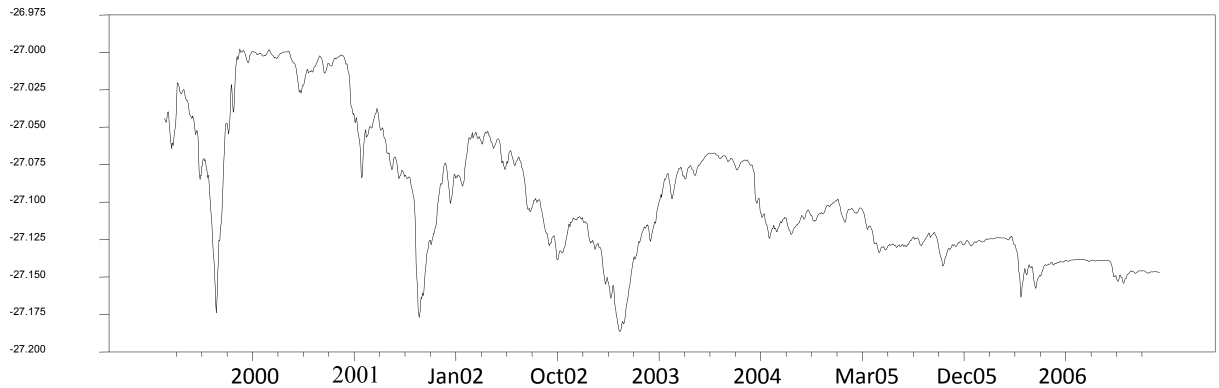
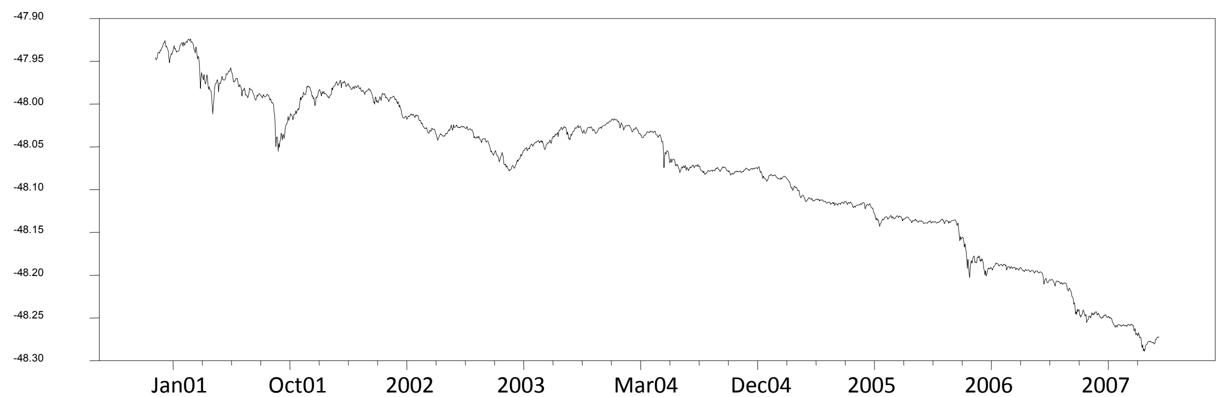


Figure 4.1: (Contd.,)

Zivot-Andrews Unit Root Tests for BSE 200 Returns



Zivot-Andrews Unit Root Tests for CNX 500 Returns



Zivot-Andrews Unit Root Tests for BSE 500 Returns

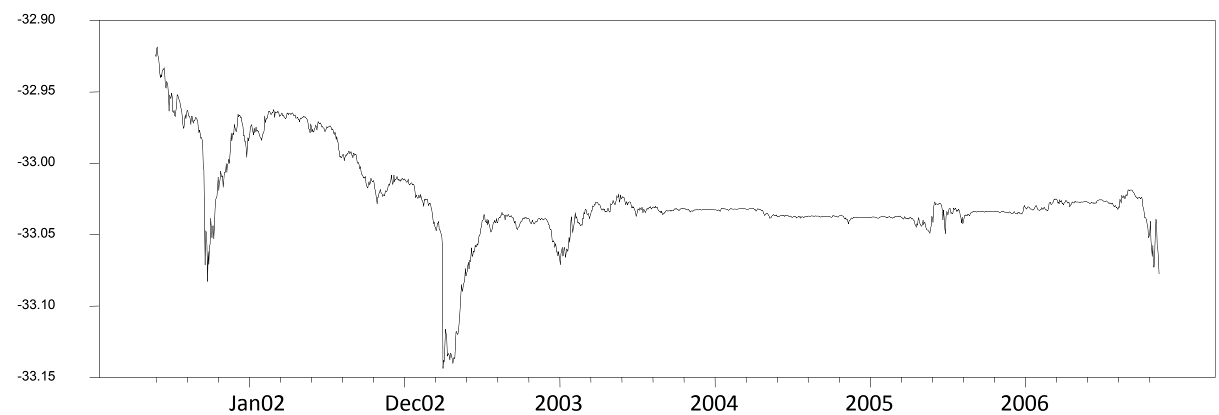
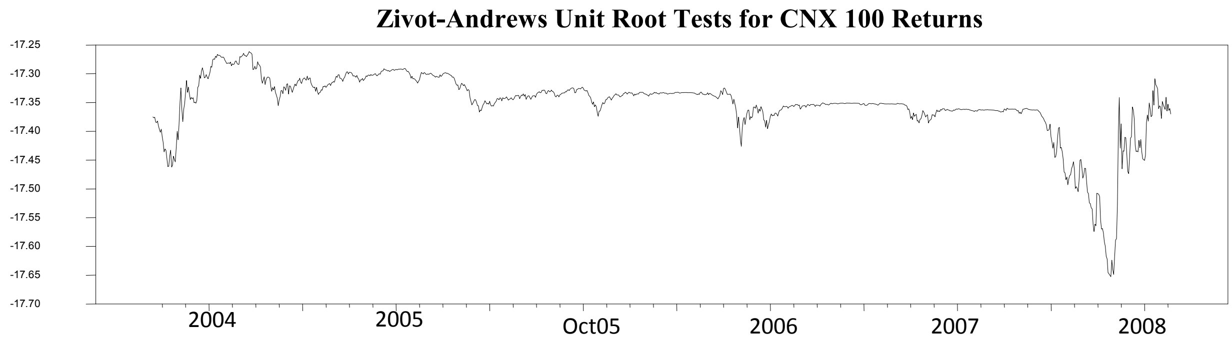
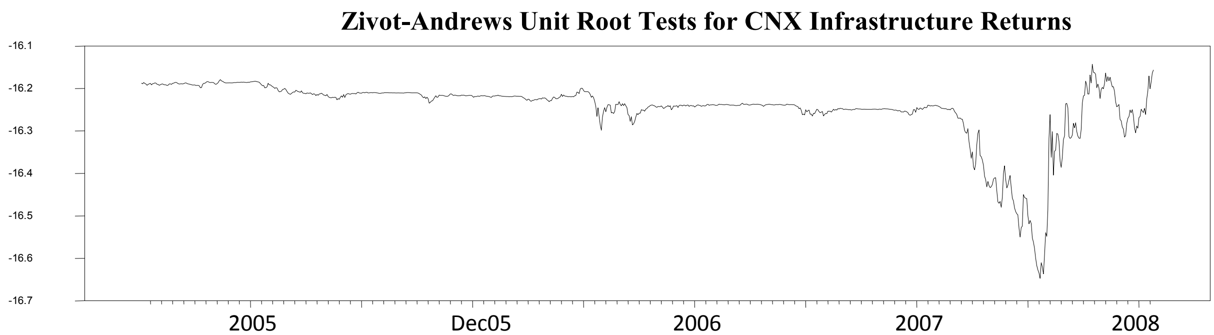
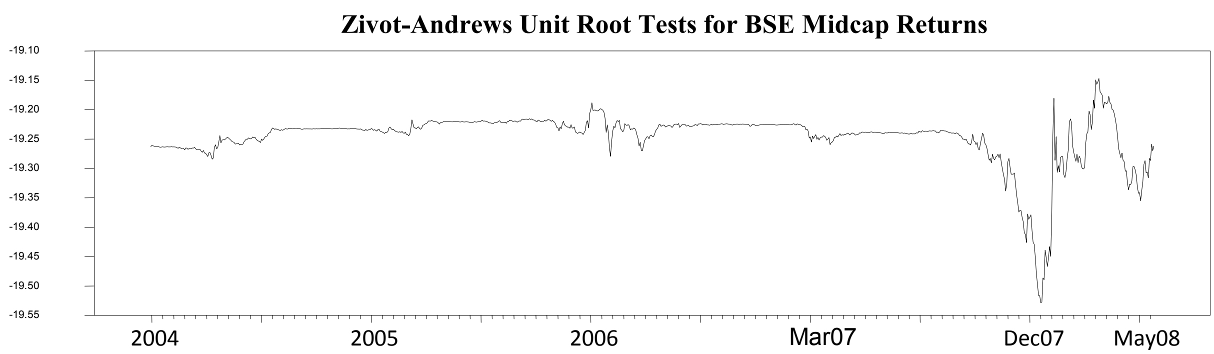
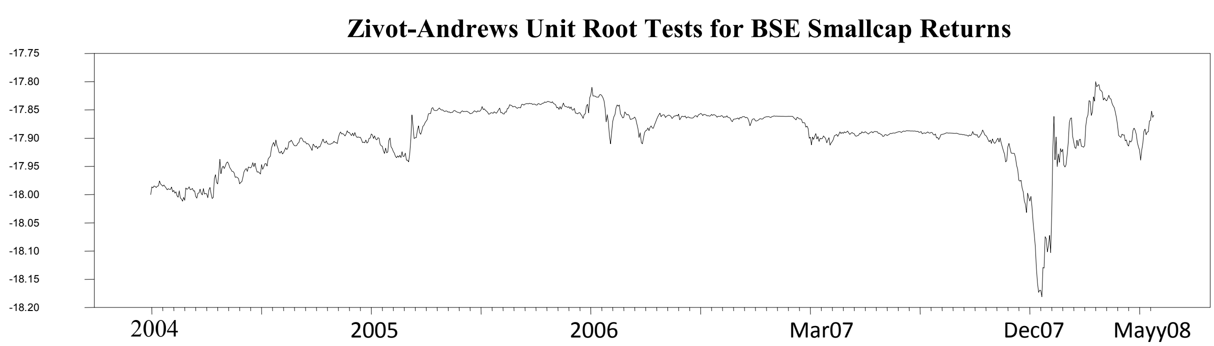


Figure 4.1: (Contd.,)









CHAPTER - 5

LONG MEMORY IN STOCK RETURNS: THEORY AND EVIDENCES

5.1 Introduction

An important aspect of stock market returns which departs from random walk hypothesis is long memory or long-range dependence which gained much attention during the past one and half decade. Long memory is a characteristic of a stationary process in which the underlying time series realizations display significant temporal dependence at very distant observations. Autocovariances of such process are not absolutely summable. The autocorrelation function of such stationary series decays hyperbolically at a slower rate. The persistent temporal dependence between distant observations indicates possibilities of predictability and hence provides opportunity to speculators to forecast future returns based on past information and make extra normal returns. Hence, presence of long memory has important theoretical and practical implications. It invalidates the EMH which states that returns are generated by a random walk process so that it is not possible to predict their future movements based on past information. The asset pricing model would also be invalid in the presence of long-memory. Besides, linear modeling would result into misleading inference in the presence of long memory. Perfect arbitrage is not possible when returns exhibit long-range dependence (Mandelbrot, 1971). Furthermore, the derivative pricing models which are based on Brownian motion and martingale process become inappropriate in the presence long-range dependence.

The issue of long memory though has important implications for theory of finance and practical applications, has not received much attention in India. With the exception of the study by Nath (2001), there is no empirical work in India. Nath's (2001) study was based on a test which has restrictive assumptions and scope of the study was confined to NSE Nifty returns. In view of the importance of long memory, it is felt more appropriate to examine the issue in the Indian context by employing a set of tests, such as Geweke and Porter-Hudak (GPH) semiparametric, Robison's Gaussian semiparametric and bias-reduced technique of Andrews and Guggenberger. Accordingly, the objective of present chapter has been set to examine the issue of long memory in mean returns of the NSE and BSE. As in the case of previous chapters, the study of long memory is confined to the period January 1997 to March 2009. The study of long memory is confined to the 14 indices from the NSE and the BSE. The rest of the chapter is organized as follows. Section - 5.2 gives a brief introduction of theory of long memory. Review of previous empirical work is presented in Section - 5.3. In Section - 5.4, testing methods employed are described. The empirical results are presented in Section - 5.5 and the last section provides the concluding remarks.

5. 2 Theory of Long Memory

5.2.1 Meaning and Definitions

There are various definitions of long memory. According to McLeod and Hipel (1978), a covariance stationary time series, R_t is said to exhibit long memory if

$$\sum_{k=-\infty}^{\infty} |\psi(k)| = \infty \qquad \ldots (5.1)$$

where $\psi\,(k)$ is the autocorrelation at lag *k*. This infinite sum condition suggests that correlation at a very distant lags cannot be ignored. Long memory is usually defined in terms of time domain and frequency domain. In time domain, a stationary discrete series R_t said to exhibit long memory if its autocovariances decay hyperbolically. In symbols

$$\psi(k) \sim k^{2d-1} \zeta_1(k), \quad k \to \infty \qquad \ldots (5.2)$$

where *d* is the long memory parameter, and $\zeta_1(.)$ is a slowly varying function.

In frequency domain, a stationary stochastic discrete time series R_t is defined by its spectral density function. This is represented as in following equation (5.3)

$$f(\omega) \sim |\omega|^{2d} \zeta_2(1/|\omega|), \quad \omega \to \infty \qquad \ldots (5.3)$$

for ω in a neighbourhood of zero and $\zeta_1(.)$ is a slowly varying function. Following Palma (2007), an alternative definition of long memory based on Wold decomposition can be given as

$$\varphi_j \sim j^{d-1} \zeta_3(j), \quad j > 0 \qquad \ldots (5.4)$$

where ζ_3 is a slowly varying function. Palma (2007) noted that further conditions are required to be imposed to make these definitions necessarily equivalent[31].

The long memory models have been in existence in physical sciences such as, geo-physics. Hurst (1951) developed a rescaled range statistics (R/S) to study long-range dependence in river flows. Mandelbrot (1972) applied R/S test, which compares the range of partial sums of deviation from the sample mean, rescaled by sample standard deviation, to stock returns. Later, Mandelbrot and Van Ness (1968), Granger and Joyeux (1980), Hosking (1981) developed stochastic models which explain dependence over a long

[31] Further discussion about these conditions can be found in Palma (2007).

period. Granger and Joyeux (1980) and Hosking (1981) introduced fractional differencing in autoregressive integrated moving average (ARIMA) framework. They developed fractional differencing model which allows a fractional value in integration order of the ARIMA model. 'The fractionally differenced process can be regarded as a halfway house between the I (0) and I (1) paradigms' (Baillie, 1996). The model is known as autoregressive fractionally integrated moving average (ARFIMA) model. The fractional parameter can be estimated from the data. This is one of the important models which is employed to examine long memory properties of times series realizations. ARFIMA model has special long memory properties which give extra potential in long run forecasting (Granger and Joyeux, 1980).

5.2.2 ARFIMA Model

Granger and Joyeux (1980), and Hosking (1981) proposed autoregressive fractionally integrated moving average (ARFIMA) model. Following Palma (2007), a time series $\{y_t\}$ follows ARFIMA (*p, d, q*) process if

$$\phi_p(\mathrm{B})\, \mathrm{y}_t = \theta_q(\mathrm{B})\, (1-\mathrm{B})^{-\mathrm{d}}\ \varepsilon_t \qquad \ldots (5.5)$$

where ϕ_p (B) = 1+ϕ_1 B . . . + ϕ_p B^p, and θ_q(B) = 1+ θ_1 B+. . . + θ_q B^q are respectively autoregressive and moving average polynomials of orders p and q, and B is back shift operator. It is assumed that the ϕ (B) and θ (B) have no common roots, $(1\text{-B})^{-d}$ is fractionally differencing operator defined by binomial expansion.

$$(1-B)^{-d} = \sum_{j=0}^{\infty} n_j\, B^j = n\,(\mathrm{B}) \qquad \ldots (5.6)$$

where

$$n_j = \frac{\Gamma\,(j+d)}{\Gamma(j+1)\Gamma(d)}$$

. . . (5.7)

where Γ denotes the gamma function. For d < ½ d≠0, -1, -2 . . . and {ε_t } is a white noise sequence with finite variance.

The parameter *d* determines the memory process. If d > 0, the process exhibits long memory. If d=0, the process has short memory and when d < 0, the process is called anti-persistent and displays negative memory. If d > -0.5, the ARFIMA process is invertible and has linear Wold representation and if d < 0.5, it is covariance stationary. Therefore, if 0<d<0.5, the process is stationary and exhibit long memory.

Various methods are used in empirical work to estimate Hurst exponent and fractional parameter. R/S statistics and modified R/S statistics proposed by Lo (1991), parametric and semiparametric tests[32], detrended fluctuations analysis (DFA) and wavelet methods are used to explore long memory process in returns.

5.3 Review of Previous Work

The first systematic empirical study of long memory was conducted by Greene and Fielitz (1977). They employed Hurst's (1951) rescaled (R/S) statistic on 200 individual stocks of New York Stock Exchange (NYSE) and found that the US stock returns contain long memory. Later, Aydogan and Booth (1988) who found no evidence of long memory concluded that the results obtained from R/S statistic are subject to the underlying restrictive assumptions of the R/S test. Randomness of S & P stock prices was assessed by

[32] Baillie (1996) reviewed long memory econometric methods.

Peters (1989). Using percentage of stock prices, he reported biased random walk (long term dependence). He attributed the observed persistence to market sentiments prevailed in the past. Later, pointing out inappropriateness of use of percentage of price in his previous paper, Peters (1992) used logarithmic returns. Nevertheless, findings of the study are in perfect agreement with the previous study. Findings of Mills (1993), however, did not support the presence of long memory in the UK stock returns, whereas Goetzmann (1993) showed that the NYSE and the LSE stock returns were characterized by long memory.

Lo (1991) challenged the findings of Greene and Fielitz (1977) and questioned the method. He demonstrated that in the presence of short run dependence in the form of heteroscedasticity, R/S test suggested by Mandelbrot (1972) is significantly a biased estimator. A modified R/S test which is robust to non-normality and heteroscedasticity was proposed by Lo (1991). The test provided contrary evidences of non-existence of long memory in the US stock returns. Lo's (1991) modified R/S test subsequently became one of the popular tests employed in empirical research to detect long-range dependence. Using both classical and modified R/S test, Ambrose *et al* (1993) rejected presence of long range dependence. Chow *et al* (1995) conducting similar tests rejected long-range dependence in series and concluded that the random walk model validly describes stock market returns behviour. Similarly, Barkoulas and Baum (1996b) have not found consistent evidence in support of long-range dependence in the US stock indices. However, the study reported fractional dynamics in individual returns series. The study was based on data of 7 sectors and daily returns of 30 companies included in Dow Jones Industrial Index. Evidences against long memory were also reported by Lux (1996) for Germany. In his investigation of long memory in 5 European, and the US and Japan, Jacobsen (1996) identified non-existence of long-term dependence with the exceptions of Germany and Italy and thus contradicted the findings of Lux (1996) for Germany. It is concluded by Hiemstra and Jones (1997) in their study that the long memory process is confined to only a tiny segment of stocks. Study by Blasco and Santamaria (1996) which covered stock returns of IGBM index of Spain, and sectoral indices for the period 1990 to 1993 observed long memory process and it was concluded by Blasco and Santamaria (1996) that during extremely long periods, evidences of long memory were weak.

In contrast to findings of these studies, Nawrocki (1995) established that major capital markets were characterized by long memory process. Further evidences of long memory characteristics were provided by Huang and Yang (1999) who carried out modified R/S statistic on intraday data of NYSE and NASDAQ. They pointed out that the presence of long memory in intraday data provides opportunities to make abnormal returns in certain intervals of trading day. Zhuang *et al* (2000) using modified R/S statistic found little evidence of long memory in British stock returns. However, the study suggested that the Great crash of 1987 has altered the time series properties in British stock market, and extra care should also be taken while analyzing the data of post war period.

The modified R/S statistics proposed by Lo (1991) has a complicated asymptotic distribution when null is true (Lobato and Savin, 1998). Furthermore, it is difficult to distinguish between short and long memory in Lo's framework. Baillie (1996) provided simulation evidences which are not favourable to Lo' (1991) approach. Researchers hence attempted to estimate fractional integration through parametric and semiparametric approaches. Cheung and Lai (1995) in addition to modified R/S analysis, employed GPH test to explore whether the findings of Lo (1991) are unique to the US or stock returns of other countries would also exhibit such dependence? The study made use of Morgan Stanley International Capital indexes of 17 countries including the US. The R/S test results resoundingly rejected long term dependence in stock returns of all 17 countries considered for study, while GPH test provided evidence of long term dependence only for 5 countries. The findings of the study are consistent with the findings of Lo (1991) and not confined to the US. The study by Barkoulas and Baum (1996a) assessed long memory presence in Japanese stock returns using spectral regression and GPH. The tests rejected long memory in mean returns. Evidences of fractional dynamics in Japan reported by Nagasayu (2003) are in total disagreements with findings of Barkoulas and Baum (1996a). The study documented evidences of long memory in Japanese stock market and concluded that financial reforms could not be able to improve efficiency as long-range dependence was detected in post reform period also. Using both Hurst (1951) exponent and modified R/S statistic, and also GPH and Robinson's frequency domain tests, Sadique and Sivapulle (2001) identified long memory in stock returns of Korea, Malaysia, Singapore and New Zealand. The parametric test of Lee and Schmidt (1996), and semiparametric methods carried out by Henry (2002) indicated presence of long memory in stock returns of Germany, Japan, South Korea and Taiwan.

Another test of long memory proposed by Labato and Robinson (1996) was applied on daily data on individual stocks in Dow Jones Industrial average by Labato and Savin (1998). The results suggested no significant long memory process. The work by Caporale and Gil-Alana (2004) used Robinson (1994) procedure to test null of absence of long memory. The results showed no evidences against null of absence of long memory for S &

P index returns. Hence, they suggested that a standard model of first difference is more appropriate for stock returns than fractional integrated model. In perfect agreement with the findings of Blasco and Santamaria (1996), De Penna and Gil-Alana (2002), based on results of Robinson (1994) test, documented evidence against long-range dependence. Christodoulou-Volos and Siokis (2006) provided strong evidence of fractional behaviour in returns series of 35 countries with a few exceptions. The study estimated fractional integration through GPH and Robinson (1995) procedures. Refuting persistence in Amsterdam, Frankfurt, Hong Kong, London, Paris, Singapore and Japan, Gil-Alana (2006) concluded that returns followed a unit root process. However, Tolvi (2003a) reported that 3 of 6 indices of OECD countries exhibit long-range dependence. He suggested that the outliers should be taken into account as otherwise potential outliers bias results. October/November of 1987 (Great Market Crash) was found to be an important outlier to bias the results of the study.

There are a few studies which used Whittle estimator and Wavelet MLE to investigate the long memory process in stock returns. A comprehensive set of tests namely, ADF, KPSS, FDF, GPH, Robinson's LM tests and Whittle and wavelet estimation procedures, was used by Necula and Altar (2002) to detect long memory. The results of the study indicated that S & P 500, NASDAQ, FTSE 100, Singapore ST and Taiwan WI, Romanian BET and BETC indices were characterized by the long memory process. In a similar fashion, Bilel and Nadhem (2009) used Whittle estimation procedure to estimate fractional integration and also performed GPH and Robison's periodogram test to examine the issue of long memory in G7 countries. The findings of the study indicated long-range dependence in returns series of 5 of the 7 markets researched.

An alternative approach namely, detrended fluctuations analysis (DFA) in addition to procedures such as classical, modified R/S and GPH, was used by Grau-Carles (2005) to probe the issue of long memory. There is no significant long-range dependence as findings suggested. The study is based on returns series of S & P 500 and Dow Jones Industrial average. To analyze the issue of long memory in daily and high frequency data returns series for the period spanning 1999-2005 and DFA method was followed by Oh *et al* (2006). They refuted long memory in returns series of 8 international stock indices.

It may be noted from the foregoing review that most of the studies not unsurprisingly have focused on well developed markets. However, it is interesting to see whether stock returns of emerging equity markets, which are supposed to posses frictions exhibit long memory properties. Relatively less developed than their developed counterparts, it is believed that stock returns of the emerging markets may be characterized by long memory process. Long-range dependence was observed in stock returns of 7 Asia-Pacific countries (Chen, 2000). The results of study by Howe *et al* (1999) indicated long-range dependence in Pacific Rim countries. Using parametric and semiparametric estimation procedures, Limam (2003) investigated long memory properties in 14 markets ranging from developed markets namely, the USA, the UK, Japan to emerging markets including Arab countries. The study suggested that long memory is more persistence in thin markets than well developed markets. Further, the study attributed the long memory process observed in Arab countries to the peculiar characteristics and environment of these economies such as weakness of regulatory framework, lack of transparency and openness to foreign investors. On similar lines, Assaf (2007) reported a fractional structure in MENA markets. Barkoulas *et al* (2000), Tolvi (2003b), Cajueiro and Tabak (2005) and

Floros *et al* (2007) reported similar findings of long-range persistence for Greek, Finnish, Brazilian and Portuguese stock markets respectively. These studies employed classical and modified R/S statistics, spectral regression, GPH, Robinson (1994) tests. Wright (1999) also observed presence of long memory in 7 of the 17 emerging markets thus supporting similar finding from these markets.

The proposition of presence of long memory in emerging markets has not remained unchallenged however. Brazil did not exhibit long memory patterns, irrespective of post Real Plan[33] (Resende and Teixera, 2002). These evidences for Brazilian stock market drew further support from Cavalcate and Assaf (2005). They established that process of equity prices cannot be explained by differences in institutions and information flows. This view was confounded by evidences from China, another important emerging market. Cajuerio and Tabak (2006) after examining Chinese data, documented strong evidences of long-range dependence in Share B and weak evidences for Share A. They attributed information asymmetry and liquidity as factors responsible for observed discrepancies. Nevertheless, Ma *et al* (2006) who applied R/S test found evidences against long memory in Chinese stock market.

Levy-stable family distribution and ARFIMA approach identified significant long memory presence in Athens stock exchange (Panas, 2001). Using Whittle estimator, Navarro Jr. *et al* (2006) came up with the conclusion that stock returns of four ASEAN markets namely, Indonesia, Malaysia, Philippines and Thailand were characterized by fractional behaviour. Ozun and Cifter (2007) employed GPH and wavelet methodologies

[33] Brazil introduced structural reforms, known as Real stabilization plan in 1994 keeping objective to stabilize macroeconomic uncertainties.

to detect long memory process in Istanbul stock exchange (Turkey). While the GPH test rejected presence of long memory, wavelet estimators provided significant evidence of long memory.

The empirical research found mixed evidences of long memory. The tests employed in the empirical works indicated strong evidence in certain markets and weak in others. Motivated by this divergence between different markets, Cajueiro and Tabak (2004) focused on relative efficiency of 8 emerging equity markets. Their analysis included computing Hurst exponents and R/S statistic and to measure relative efficiency, Spearman rank correlation was calculated. The study argued that efficiency increases proportionately with market capitalization and inversely with trading cost. Based on rank correlation coefficient, Cajueiro and Tabak (2004) ranked the US as most efficient market and concluded that Latin American markets are less inefficient than Asian markets. On similar lines of argument, using data between 1998 and 2003, Cajueiro and Tabak (2005) were set to explain the relation between efficiency and degree of development of market in Brazilian equity market. They pointed out that degree of market capitalization, return on equity and financial leverage explains presence of long memory. Furthermore, speculative behaviour and bubble in financial markets are pointed as the factors inducing long memory. The tests employed to measures such relations in these studies are not statistically powerful. Moreover, these studies do not provided any economic justification for how these things relate each other.

The review of previous work shows that the issue of long memory remains unresolved. Earlier studies probing long memory in returns series largely employed R/S test and thereafter Lo's (1991) test became popular test of long memory. Later studies exploiting ARFIMA model estimated fractional integration through various parametric and semiparametric methods. Previous works largely focused on well developed markets. Many studies pointed out that the Great crash of 1987 has altered the time series properties of returns in developed markets. The thinness of market is cited as an important factor inducing long memory in emerging Gulf markets. Some of the studies held that informational flow/asymmetry explains long memory in developing market. Although evidences from emerging markets are mixed but relatively these markets, as reported in empirical research, indicated long-range persistence. This view provides the necessary background and motivation for the present study to detect long memory in one of the fastest emerging market like India.

5.4 Testing Methods

The test of long memory in the present study is carried by utilizing the ARFIMA model. To estimate fractional integration, Geweke and Porter-Hudak (1983) semiparametric test, Robinson's (1995) Gaussian semiparametric test and, a bias-reduced log periodogram test of Andrews and Guggenberger (2003) are employed. Parametric tests require correct specification of p and q otherwise leads to inconsistent estimation of fractional integration. Therefore, Robinson (2003) suggests semiparametric tests. A brief description of the tests carried out in this study is given here.

5.4.1 Geweke and Porter-Hudak Semiparametric (GPH) Test

GPH test is simple in application and robust to non-normality. Geweke and Porter-Hudak (1983) proposed a semiparametric approach to estimate d. Under the assumption that the spectral density of stationary process may be written as

$$f(\lambda) = f_0(\lambda)[2\sin(\frac{\lambda}{2})]^{-2d} \qquad \ldots (5.8)$$

The following regression method is considered for parameter estimation [34]. Taking logarithms on both sides of (5.8) and evaluating the spectral density at the Fourier frequencies $\lambda j = 2\pi j/n$, we have

$$\log f\ (\lambda_j)\ \log\ f_0(0) - \ d \log\ \left[2\sin\frac{\lambda_j}{2}\right] + \ \log\left[\frac{f_0\ (\lambda_j)}{f_0\ (0)}\right]. \qquad \ldots (5.9)$$

On the other hand, the logarithm of the periodogram $I\ (\lambda_j)$ may be written as

$$\log I\left(\lambda_j\right) = \log\left[\frac{I(\lambda_j)}{f(\lambda_j}\right] + \ \log f(\lambda_j) \qquad \ldots (5.10)$$

Now, combining (5.9) and (5.10), it can be written as

$$\log I(\lambda_j) = \log\ f_0(0) - \ d\log\left[2\sin\frac{\lambda_j}{2}\right] + \log\left\{\frac{I(\lambda_j)\left[2\sin\left(\frac{\lambda}{2}\right)\right]}{f_{0\,(0)}}\right\} \qquad \ldots (5.11)$$

By defining $y_j = \log I\ (\lambda_j)$, $\alpha = \log f_0\ (0)$, β = -d, $x_j = \log\ [2\sin\ (\lambda_j/2)]^2$, and

$$\epsilon_j\ = \log\left\{\frac{I(\lambda_j)\ [2\sin\ \left(\frac{\lambda}{2}\right)]^{\ 2d}}{f_0\ (0)}\right\}, \qquad \ldots (5.12)$$

The following regression equation can be obtained

$$y_j\ = \propto +\beta x_j + \ \epsilon_{j.} \qquad \ldots (5.13)$$

In theory, one could expect that for frequencies near zero (that is, for j=1... m with $m<<n$

$$f(\lambda_j) \sim f_0(0)\ [2\sin(\lambda_j/2)]^2 \qquad \ldots (5.14)$$

[34] Discussion of the test is based on Palma (2007).

So that

$$\epsilon_j \sim \log\left[\frac{I(\lambda_j)}{f(\lambda_j)}\right].$$

The least squares estimate of the long memory parameter *d* is given by

$$\hat{d}_m = -\frac{\sum_{j=1}^{m}(x_j-\bar{x})(y_j-\bar{y})}{\sum_{j=1}^{m}(x_j-\bar{x})^2} \qquad \text{. . . (5.15)}$$

where $\bar{x} = \sum_{j=1}^{m} x_j / m$ and $\bar{y} = \frac{\sum_{j=1}^{m} y_j}{m}$.

The bandwidth *m* must be chosen such that for $T \rightarrow \infty$, $m \rightarrow \infty$, $m/T \rightarrow 0$. The estimates are sensitive to the number of special ordinates from periodogram of returns (*m*). The GPH in the present study is performed choosing values m=T, $^{5.0}$ T,$^{5.5}$ and T $^{6.0}$

5.4.2 Robinson's Gaussian Semiparametric (RGSE) Test

Robinson (1995) suggested Gaussian semiparametric estimate of the self-similarity parameter H. It is assumed that the spectral density of the time series, denoted by *f* (.), behaves as

$$f(\lambda) \sim G\lambda^{1-2H} \quad \text{as } \lambda \rightarrow 0^{+} \qquad \text{. . . (5.16)}$$

for G ∈ (0,∞) and H ∈(0,1). The self-similarity parameter H relate to the long memory parameter *d* by H=d+1/2. The estimate for H, denoted by $\hat{H}$, is obtained through minimization of the function

$$R(H) = \log \hat{G}(H) = \frac{1}{v}\sum_{\delta=1}^{v} \log \lambda_\delta \qquad \text{. . . (5.17)}$$

With respect to H, where $\hat{G}(H) = \frac{1}{v}\sum_{\delta=1}^{v} \lambda_{\delta}^{2H-1} I(\lambda_{\delta})$. The discrete averaging is carried out over the neighbourhood of zero frequency and, v is assumed to be tending to infinity much more slowly than does T under asymptotic theory. The Gaussian semiparametric proposed by Robinson (1995) is consistent under mild conditions and is asymptotically normal.

5.4.3 Andrews and Guggenberger Bias Reduced (AGBR) Test

A bias reduced log periodogram estimator is proposed by Andrews and Guggenberger (2003). The method is the same as that of GPH estimator except that it included frequencies to the power 2k for k=1,2...,r, for some positive integer r, as additional regressors in the pseudo regression model that yields GPH estimators. This estimation method eliminates the first and higher order biases of GPH estimator.

The fundamental frequencies for a sample size *n* denoted as

$$\lambda_j = \frac{2\pi_j}{n} \text{ for } j = 1, \dots, [\frac{n}{2}] \qquad \dots (5.18)$$

The estimator $\hat{d}_r$ (of the long memory) is defined to be the least squares estimator of the coefficient on -2log λ_i in a regression of log of the periodogram.

The AGBR adds regressors λ_j^2 $\lambda_{j\dots,}^3\lambda_j^{2r}$ to the regression model. When r=0, d_r is asymptotically equivalent to the standard GPH. Andrews and Guggeneberger (2003) suggest that bias-reduced log-periodogram estimator performs well for the small values of r such as r=1 and r=2.

5.5 Indian Evidences

As table 2.1 shows that index returns are non-normal, the GPH test of long memory assumes relevance as it is robust to non-normality. The GPH test is performed on the daily stock returns of 14 indices and the results are reported in table 5.1. The number of special ordinates from periodogram of returns (*m*) to include in the estimation of *d* must be chosen judiciously as otherwise they produce inaccurate estimation of *d*. The value of *d* is estimated choosing m=$T^{5.0}$, $T^{5.5}$ and $T^{6.0}$. It is clearly evident from the table that long-range dependence structure exists in most of the stock indices. The values for all stock indices are positive and ranges between lowest 0.021 for CNX Bank Nifty to highest 0.228 for CNX Infrastructure. However, the value of *d* for CNX Nifty is negative at m=.5 and .55 and for CNX Defty it is negative at *m*=.5. This may be due to sensitiveness of the test to the chosen ordinates. Broadly, the results indicate long memory in stock returns.

The test statistics of Robinson's Gaussian semiparametric estimates of *d* are provided in table 5.2. The value of *d is* estimated using $T^{0.75}$, $T^{0.8}$ and $T^{0.9}$. The results obtained from RGSE are quite different from GPH test results. The value of fractional differencing parameter *d* is within the theoretical value. However, estimated *d* reported for BSE Sensex, BSE 200, CNX 500 and CNX 100 at $T^{0.75,}$ and for BSE 100, Bank Nifty and CNX Infrastructure at $T^{0.75 \text{ and}}$ $T^{0.80}$ is negative in this case. These negative values of *d* suggest anti-persistence. The remaining stock returns series are characterized by long memory process.

Furthermore, AGBR test is employed on stock returns of all fourteen indices from the NSE and the BSE. The AGBR test substantially mitigates the finite sample bias. In other words, it eliminates the first and higher order biases of GPH. The value of d is estimated with r=1 and r=2 and the results are furnished in table 5.3. It can be observed from the table that the value of d is less than 0.5 and thus indicating presence of long range dependence. The value of d is ranging between 0.04 for CNX Nifty to 0.38 for CNX 500. Nevertheless, negative value of fractional parameter are evident from table 5.3 for CNX Nifty and CNX Nifty Junior at r=1, and BSE 500 and CNX Infrastructure at r=1 and r=2. The results from AGBR thus are in consonance with the results obtained from GPH and RGSE which also indicated long memory.

The empirical results provide mixed evidences of long-range dependence in stock returns of different indices traded at BSE and NSE. The anti-persistence evidences are not consistent for tests conducted. However, broadly, this indicates that there exists a tendency for stock returns to returns to its trend path.

5.6 Concluding Remarks

The present paper attempted to examine the issue of long memory in Indian stock market. The study employed three tests namely, Geweke and Porter-Hudak (1983), Gaussian semiparametric test of Robinson (1995) and Andrews and Guggenberger (2003) for 8 indices of NSE and 6 indices of BSE. Mixed evidences for indices are provided by GPH and RGSE test. The tests results of AGBR are quite definite and suggest long range dependence. The findings of the study by and large suggest existence of long memory in mean returns of the most of the indices. Furthermore, there are no significant and consistent evidences which could suggest that smaller indices are generally characterized by long memory process. It may be inferred from the findings that stock returns in India are not characterized by random walk process. It implies that the two exchanges are not weak form efficient. The tendency of mean-reversions indicates the possibility of prediction and speculation in these two premier markets. This has a practical implication for market participants. It implies potential prediction of future returns over a longer period. The use of linear model in the presence of long memory would result in misleading inferences.

Table 5.1: Estimates of Fractional Differencing Semiparameter '*d*' (GPH)

Index Returns	GPH Estimator		
	***m*=0.50**	***m*=0.55**	***m*=0.60**
CNX Nifty	-0.119	-0.050	0.034
CNX Nifty Junior	0.039	0.075	0.161
CNX Defty	-0.022	0.034	0.089
CNX IT	0.051	0.052	0.066
BSE Sensex	0.068	0.076	0.102
BSE 100	0.045	0.075	0.114
BSE 200	0.038	0.061	0.101
CNX 500	0.006	0.023	0.077
CNX Bank Nifty	0.014	0.086	0.075
BSE 500	0.021	0.130	0.165
CNX 100	0.195	0.171	0.143
CNX Infrastructure	0.228	0.207	0.103
BSE Midcap	0.164	0.114	0.108
BSE Smallcap	0.093	0.054	0.111

Note: Value in each cell of the table represents fractional integration, *d,* estimated by GPH semiparametric method. The values of'*d*' obtained by choosing m=$T^{5.0}$, $T^{5.5}$ and $T^{6.0}$, T. *m is* special ordinates from periodogram of returns.

Table 5.2: Robinson Gaussian Semiparametric Estimation of '*d* '

Index Returns	RGSE		
	0.75	**0.8**	**0.9**
CNX Nifty	-0.007	0.020	0.020
CNX Nifty Junior	0.023	0.057	0.077
CNX Defty	0.010	0.036	0.036
CNX IT	0.021	0.014	0.018
BSE Sensex	-0.018	0.015	0.025
BSE 100	-0.011	-0.007	-0.08
BSE 200	-0.173	-0.233	-0.35
CNX 500	-0.001	0.009	0.018
CNX Bank Nifty	-0.053	-0.004	0.050
BSE 500	0.033	0.055	0.075
CNX 100	-0.006	0.011	0.044
CNX Infrastructure	-0.002	-0.007	0.039
BSE Midcap	0.069	0.065	0.130
BSE Smallcap	0.103	0.115	0.196

Note: The values given in the table are the estimates of'*d*' computed following RGSE method. These values are obtained by conducting tests with power, 0.75, 0.8 and 0.9.

Table 5.3: Andrews and Guggenberger Biased Reduced Estimation of '*d*'

Index Returns	r=1	r=2
CNX Nifty	-0.074	0.040
CNX Nifty Junior	-0.032	0.008
CNX Defty	0.0379	0.123
CNX IT	0.036	0.074
BSE Sensex	0.141	0.180
BSE 100	0.097	0.112
BSE 200	0.116	0.143
CNX 500	0.132	0.389
CNX Bank Nifty	0.095	0.371
BSE 500	0.048	-0.008
CNX 100	0.031	0.264
CNX Infrastructure	0.145	-0.020
BSE Midcap	0.080	0.205
BSE Smallcap	0.096	0.028

Note: The biased reduction estimation is performed with bandwidth *m* equal to square root of the number of observations. Andrews and Guggenberger (2003) suggest small values of r for better performance of the estimation. Accordingly test is performed with r=1, and 2, r being the non-negative integer.

CHAPTER - 6

LONG MEMORY IN VOLATILITY

6.1 Introduction

The rapid growth of emerging markets in recent past, and increasing importance of these markets in global finance have attracted the attention of investors. As a result, there has been increasing interest among researchers, investors, and practitioners to understand these markets. Stock markets of emerging economies are generally characterized by thin-trading, various frictions and high volatility. Highly volatile market negatively affects an economy. Volatility hence is an indicator of vulnerability of financial markets and the economy. Policy makers, therefore, time and again rely on such an indicator (Poon and Granger, 2003). Log-squared, squared returns and absolute returns are used as proxies of returns volatility in empirical studies. The autocorrelation of these returns appears to decay at a slower rate. Slow mean-reverting hyperbolic rate decay in autocorrelation functions of squared, log-squared returns defined as long memory in variance or volatility process.

Modeling long memory in volatility has gained much importance in recent years due to its practical implications. Standard generalized autoregressive conditional heteroscedastic (GARCH) models do not account for long memory in volatility. Consequently, the risk-returns analysis using such models would lead to misleading inferences in the presence of long memory in variance. Further, volatility is an important input in derivative pricing, portfolio and risk management strategies and also vital in business cycles. Mendes and Kolev (2006) showed that presence of long memory masks the true dependence structure in emerging markets.

In the light of the this, the present chapter aims to probe long memory in volatility in Indian equity market. For convenience, the rest of chapter is organized on following track. Section 6.2 presents a brief review of previous work on long memory volatility process particularly from emerging markets. Section 6.3 describes the methodology followed. Empirical results for India are presented in Section 6.4 and Section 6.5 provides concluding remarks. Towards the end of this chapter, summary, major findings and implications of the study are presented.

6.2 Review of Previous Work

Present section presents a brief review of previous work particularly recent studies from emerging markets. Many studies focused on developed markets particularly the US, reported that the stock returns are characterized by long memory in volatility. [See, Ding *et* al, 1993; Crato and Lima, 1994; Ding and Granger, 1996; Andersen and Bollerslev, 1997; Granger *et al,* 1997; Comte and Renault, 1998; Lobato and Savin, 1998; Andersen *et al*, 2003 among others]. Andreano (2005) exploited Bollerslev and Jubinski (1999) model to explain long memory process in Italian stock market and proved the long memory process in volatility and volume. Oh *et al* (2006) focused on 8 international indices both from developed and also from emerging markets[35]. The study carried out DFA method and was based on daily data covering the period 1991 to 2005 for all indices and also used 1 minute high frequency data for Korean Index (KSOPI). The DFA test results suggested strong evidence of long memory. Oh *et al* (2006) concluded that volatility clustering is inducing long memory in volatility process.

[35] These indices are namely, S & P 500, NASDAQ, Hengseng, Nikkie 225, DAX, CAC40, FTSE 100 and KOSPI.

The time series properties of stock returns in emerging markets are expected to be different from that of developed markets because of their certain peculiar characteristics. There has been little focus on issue of long memory in these markets. However, recent studies from emerging markets have provided some evidences of long memory in volatility. Cavalcante and Assaf (2005) who utilized Baillie *et al* (1996) model on a sample between 1997 and 2002 on Brazilian stock market, reported strong dependence in absolute and squared returns. Using data between 1995 and 2005 of 12 emerging markets, Mendes and Kolev (2006) examined long memory in volatility. The study which employed Baillie *et al* (1996) model evidenced strong presence of long memory in volatility in these markets. MENA markets namely, Egypt, Jordon, Morocco and, Turkey exhibited significant long memory in volatility (Assaf, 2007). However, the study concluded that the long memory is not because of sudden shifts in variance (Assaf, 2007). This view was supported by Kang and Yoon (2008) who argued that the long memory in volatility is inherent in data generating process and it is not because of any shocks. In contrast, Korkmaz (2009) proved long memory volatility characterization of stock index returns on Turkey for unfiltered data but weak evidence of long memory for filtered data after treating structural breaks properly. The study, thus, argued that long memory in volatility is the result of occurrence of structural breaks.

Evidence of long memory in returns volatility is also reported for Turkey.[36] Killic (2004) set out to examine the issue of long memory volatility process in Turkey. Using data of the period 1988 to 2003 and FIGARCH model, the study indicated presence of long memory volatility process and concluded that FIGARCH model better represents the long memory than GARCH specification. Extending the data period up

[36] Studies relating to Turkey used data on Istanbul Stock Exchange.

to 2007, Kasman and Torun (2007) reported long memory process both in returns and volatility. These findings of long memory characterization of volatility process in Turkey drew further support from DiSario *et al* (2008). Long memory characterization of volatility was also established by Floros *et al* (2007) for Portuguese. The study was based on data covering the period from 1993 to 2006 of BVLP stock exchange. However, data for sub-period, from 2002 to 2006 showed weaker evidence of long memory in volatility. Floros *et al* (2007) attributed such evidences to merger of BVLP with Euronext 2002. Gurgul and Wojtowicz (2006) in their study concluded that the presence of long memory in German stock exchange is due to increase in institutional investors on German market which led to risk-level reduction. They carried out a study on stocks listed in DAX 30 of Germany.

Empirical evidences of long memory in volatility for African markets are mixed. Jefferis and Thupayagale (2008) offered evidences of long memory in volatility for South Africa and Zimbabwe. But no such evidences found in Botswana indicating unpredictability of future volatility based on past values. In their investigation of African markets, McMillan and Thupayagale (2009) found evidence of long memory in volatility in 7 of 11 African markets researched. Illiquidity and trading conditions in these markets are considered as factors responsible for such long memory. Against backdrop of economic reforms in South Africa, McMillan and Thupayagale (2008) investigated the issue of long memory in volatility. For the purpose, the study divided the data into pre and post reform period. The results suggested long memory in volatility for both pre and post reform period. They concluded that behaviour of stock returns in South Africa is continued to be driven by risk.

The evidences from emerging markets provide significant and robust presence of long memory in volatility. However, there has been no comprehensive study of long memory in volatility in India which is one of the fastest growing emerging markets, till date. Hence, the present chapter is devoted to the issue of long memory in volatility in the two premier Indian stock exchanges namely, NSE and BSE. India considered as one of the important emerging economies, has made tremendous growth in recent past. The financial sector reforms have given much impetus for the growth of stock market. Several market microstructure changes have taken place during the past two decades including establishment of NSE in 1994. The NSE and the BSE introduced nation-wide screen based automated trading system. Derivative instruments were introduced in 2000 in order to improve risk management and efficiency. The FIIs have been permitted to invest in Indian capital market. Given these changes, the study of long memory volatility in Indian equity market is appropriate.

6.3 Methodology

Volatility typically has a fractional value. In other words, squared returns or absolute returns which are used as measure of volatility typically have autocorrelations which decay at slow hyperbolic rate. The conventional autoregressive conditional heteroscedasticity or ARCH models cannot capture the slow decay of autocorrelation function in conditional variance. Robinson (1991) extended fractional integrated ARMA or ARFIMA due to Granger and Joyeux (1980) and Hosking (1981) process for mean, to model long memory in volatility. Based on framework of ARFIMA, a fractionally integrated GARCH or FIGARCH model is proposed by Baillie *et al* (1996). A brief description of the model is given in this section.

6.3.1 FIGARCH Model

The standard GARCH (*p, q*) model in ARMA for squared errors can be written as

$$[1 - \alpha\ (\mathrm{B}) - \beta(\mathrm{B})\ \varepsilon_t^2 = \omega + [1 - \beta(\mathrm{B})]v_t \qquad \ldots (6.1)$$

where B is the back shift operator, $1 - \alpha(\mathrm{B}) - \beta(\mathrm{B})$ is autoregressive lag polynomial and $[1-\beta(\mathrm{B})]$ is moving average polynomial and, $\nu_t \equiv \varepsilon_t^2 - \sigma_t^2$ is mean zero serially uncorrelated. Thus the $\{\nu_t\}$ process is integrated as the "innovations" for the conditional variance. All the roots $[1-\alpha(\mathrm{B})-\beta(\mathrm{B})]$ and $[1-\beta(\mathrm{B})]$ are constrained to lie outside the unit circle in order to ensure stability and covariance stationary of the $\{\varepsilon_t\}$ process. When autoregressive lag polynomial, $1-\alpha(\mathrm{B})-\beta(\mathrm{B})$ contains a unit root, the model becomes integrated GARCH or IGARCH model of Engel and Bollerslev (1989). This is given by

$$\phi(\mathrm{B})(1-\mathrm{B})\varepsilon_t^2 = \omega[1+\beta(\mathrm{B})]\nu_t \qquad \ldots (6.2)$$

Similar to ARFIMA process for the mean, introducing a difference operator $(1-\mathrm{B})^{\bar{d}}$ in the equation (6.2), fractionally integrated GARCH or FIGARCH (*p q d*) model can be specified as

$$\phi(\mathrm{B})(1-(\mathrm{B})^{\bar{d}}\varepsilon_t^2 = \omega + [1-\beta(\mathrm{B})]\nu_t \qquad \ldots (6.3)$$

where $\phi(\mathrm{B})$ and $\beta(\mathrm{B})$ are polynomial in B of orders *p* and *q* respectively, ϕ, β, ω and *d* are parameter to be estimated. In equation (6.3), ν_t is a mean-zero, serially uncorrelated process, and $0<d<1$. The FIGARCH captures a slow hyperbolic rate of decay for the autocorrelations of ε_t. FIGRARCH model reduced to GARCH when $\bar{d}$ = 0 and to the IGARCH when $\bar{d}$ = 1. Baillie *et al* (1996) through simulations demonstrated that Quasi maximum likelihood (QMLE) estimation method performs better in case of high frequency financial data.

6.4 Empirical Results

The daily closing values of indices both from the NSE and the BSE are presented in figure 6.1. It is evident from the figure that most of the indices followed the same pattern. A slowly increasing uptrend growth can be observed in all indices which reached highest peak in mid-2007. This was a period when BSE Sensex and

CNX Nifty touched highest benchmark. In post mid-2007, there has been downward slope in daily values and the slope is significantly steep. The downward slope is steeper for BSE 200 and CNX 500. The daily closing values of CNX IT registered sudden uptrend during 1999-2000 and thereafter stock prices for CNX IT are fluctuating and almost straight line can be seen since 2004. Graphical representation of daily stock returns of indices is presented in figure 6.2 for further understanding volatility persistence. Occurrence of tranquil and volatile periods is clearly evident from figure 6.2. This indicates volatility clustering in Indian exchanges, which is well acknowledged stylized fact of stock returns.

The descriptive statistics for the 14 index returns are given in table 2.1. The table shows that BSE 200 has the highest standard deviation, followed by CNX IT indicating high volatility, and lowest is of CNX Nifty and BSE Sensex (see table 2.1). The volatility especially increased during 2007 and 2008 for all stock return indices (see figure 6.2). The returns of all indices are negatively skewed implying the returns are flatter to the left compared to normal distribution (see table 2.1).

The objective of the present chapter is to detect long memory in volatility process. The presence of long memory in variance is tested by estimating FIGARCH model of Baillie *et al* (1996). For a comparison purpose, GARCH and IGARCH model estimations are also presented. QMLE method is used for estimation, as Baillie *et al* (1996) demonstrated that this method provides better estimation. Results of estimated GARCH (1, 1) model are given in table 6.1. The results support the presence of time-varying volatility as the estimated GARCH coefficient is significant as indicated by test significant values given in the parentheses for all the indices (see, table 6.1). The value of autoregressive parameter in the conditional variance equation, ϕ is close to unity for all indices (indeed it is unity for BSE Midcap) indicating volatility persistence. The value of conditional variance equation which is close to unity suggests IGARCH behaviour. To examine this and for a comparison purpose, IGARCH (1, 1) model is estimated and statistics are furnished in table 6.2. The estimates for IGARCH model are quite similar to estimates of GARCH model given in table 6.1. Baillie *et al* (1996) cautioned that such kind of results may lead one to infer that IGARCH model provide a satisfactory description of the volatility process. Keeping this caveat in mind, FIGARCH model is estimated.

Table 6.3 reports estimates for FIGARCH model. It can be seen from the table that with the exception of BSE 500, CNX 100, CNX Infrastructure and BSE Midcap, the fractional difference parameter, d is significantly within the theoretical value (i.e. $0<d<0.5$) for all other index returns. The value of d ranged between lowest 0.36 for CNX Bank Nifty to highest 0.49 for CNX Nifty Junior. These results show presence of long memory in volatility in Indian equity market. The value of fractional difference parameter for indices namely, BSE 500 (0.56), CNX 100 (0.71), CNX Infrastructure (0.69) and BSE Midcap (0.57) is greater than theoretical value of long memory ($0<d<0.5$) . Further, a one sided t-test for d = 1.0 against 1.0 in FIGARH model clearly rejected the IGARCH null hypothesis against FIGARCH model estimated here. FIGARCH model, therefore, better describes volatility persistence than conventional ARCH class models. The value of d appears to be lower for larger sized and liquid indices such as CNX Bank Nifty (0.36), CNX Defty (0.40), CNX Nifty (0.43), BSE Sensex (0.44), and Nifty Junior (0.49), while for other smaller indices, it ranges between 0.5 to 0.7 (see table 6.3).[37]

[37] This kind of possibility is demonstrated by certain studies. See Matteo *et al,* 2003, 2005. However, in the present context, the inferences are suggestive.

The stock returns on both NSE and BSE posses long memory in volatility. This indicates possibility of predictable components based on past volatility. The evidences of long memory in volatility indicate persistence of shocks for long period. This as Poon and Granger (2003) pointed out that long memory in volatility implies that shock to volatility process would have a long-lasting impact. This shows the importance of treating long memory in volatility in monetary policy measures. It has important theoretical and practical implications. The predictable component in volatility violates EMH. Volatility is an important input in the option pricing formulas such as Black and Sholes. Similarly, the Value at Risk models and risk-return studies commonly use short memory for filtering. The long memory in volatility, thus, suggestive in deriving pricing formulas and should be treated properly while modeling risk management.

6.5 Concluding Remarks

The purpose of this chapter is to investigate empirically the long memory in volatility in two premier stock exchanges namely, NSE and BSE in India, in light of several macro economic and market microstructure changes. The empirical analysis found long memory in variance of returns in 7 out of 14 indices examined. This implies predictability of future volatility based on distant memory of volatility. The value of fractional integration appears to be higher for small indices and, lower for larger indices. It is to be noted that relatively active stocks which are considered as barometer of market exhibited long memory in volatility. On policy front, improving liquidity of medium and small sized indices is essential. The proper modeling of long memory in volatility is essential for deriving pricing and, value at risk modeling.

Figure 6.1: Daily Closing Values of Return Indices of NSE and BSE

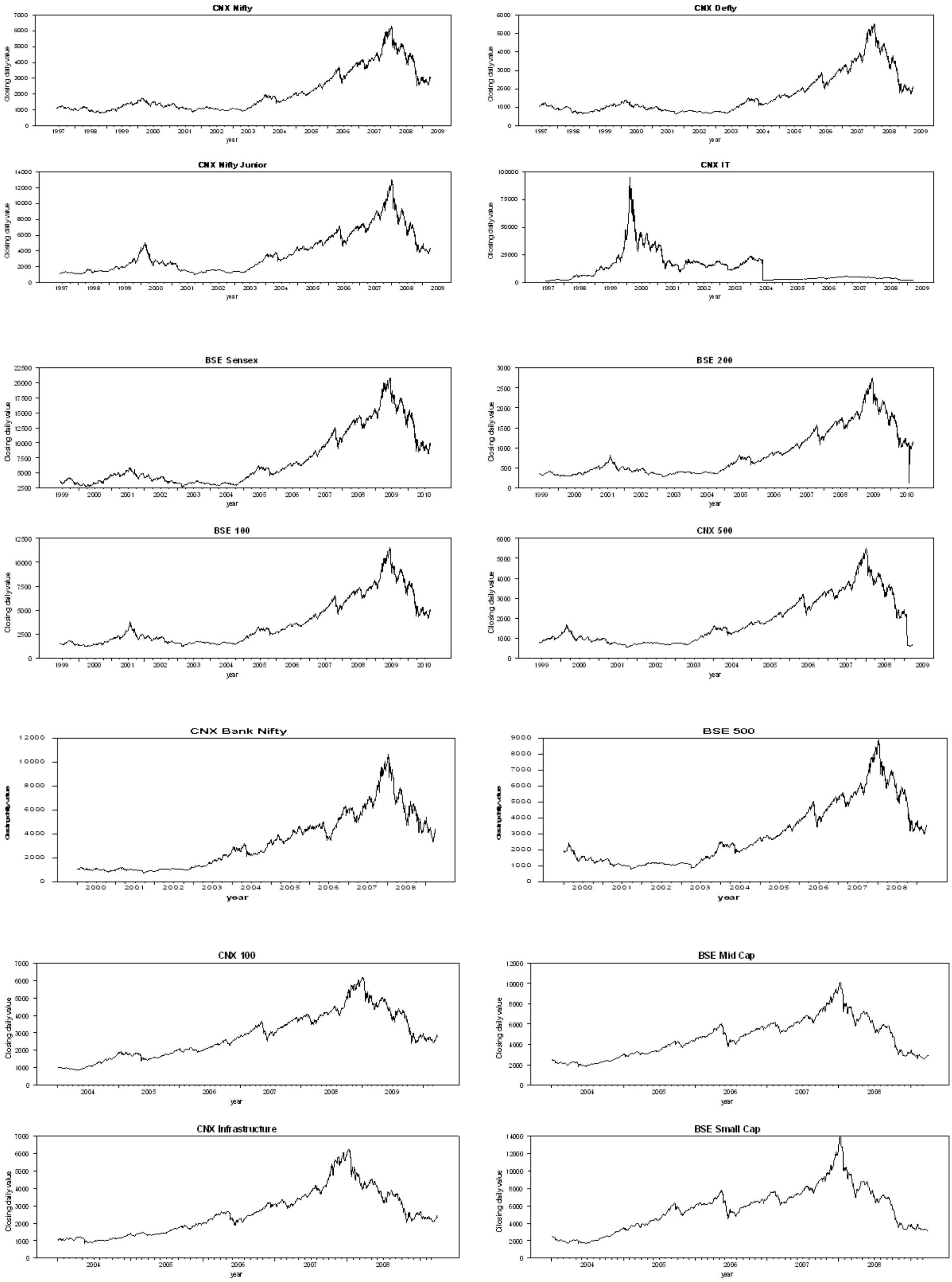


Figure 6.2: Daily log Return of Indices of NSE and BSE

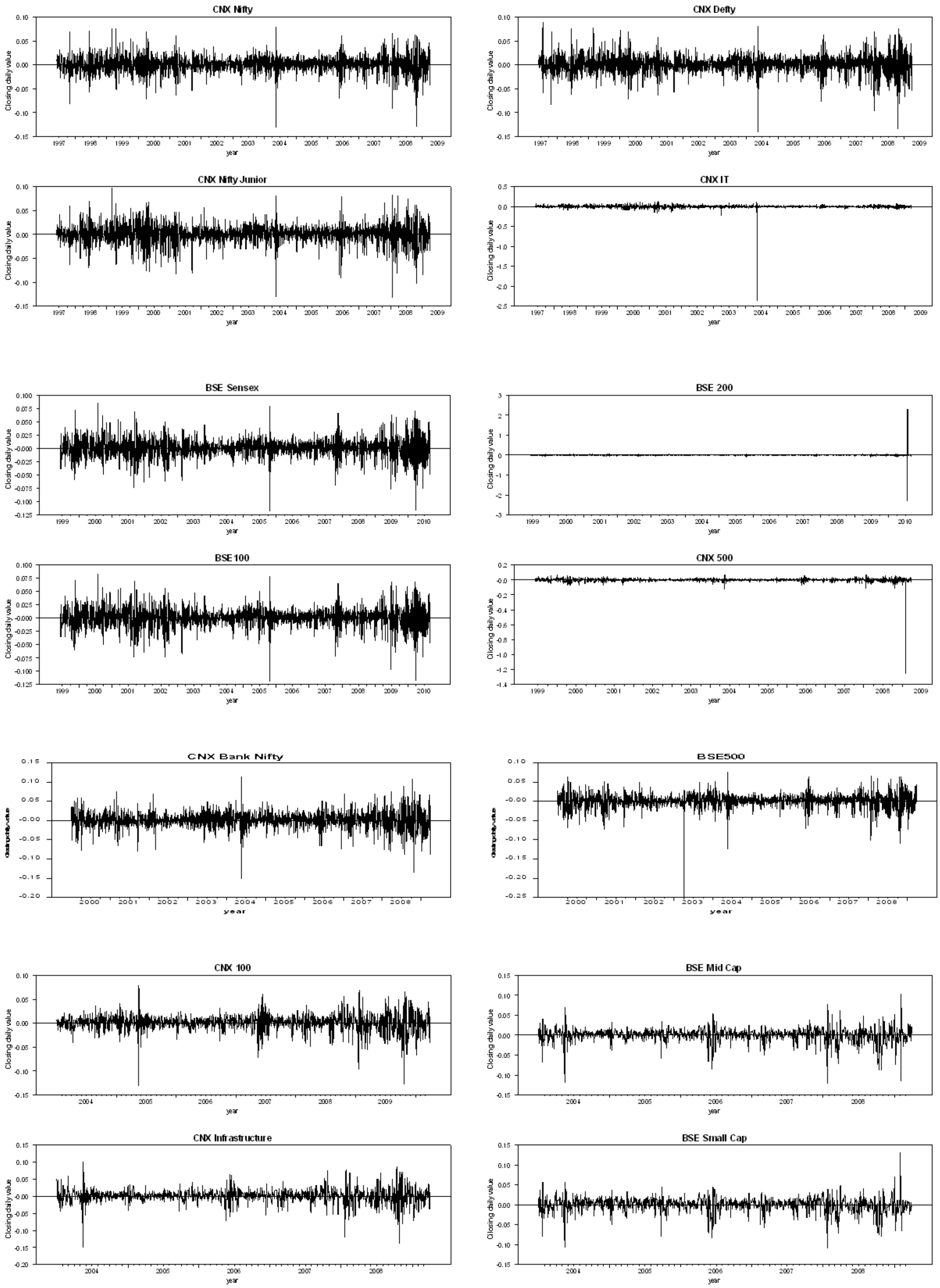


Table 6.1: Estimates of GARCH Model

Index Returns	Mean	C	ϕ	β	*d*	Q (20)	Q^2 (20)
CNX Nifty	0.0013	0.0000	0.9702	0.8135	-	62.36	15.25
	(0.000)	(0.001)	(0.000)	(0.000)		(0.000)	(0.762)
CNX Nifty Junior	0.0015	0.0000	0.9695	0.7863	-	125.26	23.10
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.283)
CNX Defty	0.0014	0.0000	0.973	0.814	-	59.94	15.16
	(0.000)	(0.001)	(0.000)	(0.000)		(0.000)	(0.767)
CNX IT	-	-	-	-	-	-	-
BSE Sensex	0.0014	0.0000	0.9773	0.8301		60.81	25.64
	(0.000)	(0.002)	(0.000)	(0.000)		(0.000)	(0.177)
BSE 100	-	-	-	-	-	-	-
BSE 200	-	-	-	-	-	-	-
CNX 500	-	-	-	-	-	-	-
CNX Bank Nifty	0.0011	0.0000	0.9801	0.8698	-	66.10	24.56
	(0.002)	(0.014)	(0.000)	(0.000)		(0.000)	(0.219)
BSE 500	0.0022	0.0000	1.0162	0.6068	-	84.50	2.73
	(0.000)	(0.034)	(0.000)	(0.000)		(0.000)	(0.999)
CNX 100	0.0018	0.0000	0.980	0.817	-	40.71	32.59
	(0.000)	(0.008)	(0.000)	(0.000)		(0.004)	(0.037)
CNX Infrastructure	0.0021	0.0000	0.989	0.803		51.49	35.28
	(0.000)	(0.025)	(0.000)	(0.000)		(0.000)	(0.018)
BSE Midcap	0.0022	0.0000	1.008	0.759	-	75.71	23.02
	(0.000)	(0.129)	(0.000)	(0.000)		(0.000)	(0.287)
BSE Smallcap	0.0022	0.0000	0.9860	0.7992	-	101.19	24.61
	(0.000)	(0.168)	(0.000)	(0.000)		(0.000)	(0.217)

Note: The table reports the Quasi maximum likelihood estimates (QMLE) for GARCH (*p, q*) model for the stock return on the various indices of NSE and BSE. C denotes constant in variance equation, β represents GARCH (lagged variance) parameter, ϕ denotes autoregressive parameter in conditional variance equation. The values in the parentheses represent significance level. Q (20) and Q^2(20) refer to the Ljung-Box portmanteau tests for up to 20th order serial correlation in the standardized and squared standardized residuals, respectively. GARCH model could not be estimated for CNX IT, BSE 100, BSE 200 and CNX 500.

Table 6.2: Estimates of IGARCH Model

Index Returns	Mean	C	ϕ	β1	*d*	Q(20)	$Q^2(20)$
CNX Nifty	0.0014 (0.000)	0.0000 (0.000)	-	0.8200 (0.000)	1	63.26 (0.000)	18.59 (0.548)
CNX Nifty Junior	0.0015 (0.000)	0.0000 (0.000)		0.792 (0.000)	1	124.07 (0.000)	26.41 (0.153)
CNX Defty	0.001 (0.000)	0.0000 (0.000)		0.819 (0.000)	1	61.03 (0.000)	18.24 (0.571)
CNX IT	-	-	-	-	-	-	-
BSE Sensex	0.0014 (0.000)	0.0000 (0.004)		0.837 (0.000)	1	61.97 (0.000)	28.41 (0.100)
BSE 100	-	-	-	-	-	-	-
BSE 200	-	-	-	-	-	-	-
CNX 500	-	-	-	-	-	-	-
CNX Bank Nifty	0.0011 (0.010)	0.0000 (0.006)	-	0.8793 (0.000)	1	65.11 (0.000)	26.45 (0.151)
BSE 500	0.002 (0.001)	0.0000 (0.071)		0.606 (0.000)	1	84.70 (0.000)	2.52 (0.999)
CNX 100	0.002 (0.000)	0.0000 (0.004)	-	0.819 (0.000)	1	40.38 (0.004)	30.75 (0.059)
CNX Infrastructure	0.002 (0.000)	0.0000 (0.021)	-	0.804 (0.000)	1	51.01 (0.000)	34.04 (0.025)
BSE Midcap	0.0022 (0.000)	0.0000 (0.076)	-	0.7590 (0.000)	1	76.43 (0.000)	23.35 (0.272)
BSE Smallcap	0.0022 (0.000)	0.0000 (0.063)	-	0.8010 (0.000)		98.97 (0.000)	24.15 (0.236)

Note: The table reports the Quasi maximum likelihood estimates (QMLE) for IGARCH model for the stock return on the various indices of NSE and BSE. C denotes constant in variance equation, β represents GARCH (lagged variance) parameter, ϕ denotes autoregressive parameter in conditional variance equation. The values in the parentheses represent significance level. Q (20) and $Q^2(20)$ refer to the Ljung-Box portmanteau tests for up to 20^{th} order serial correlation in the standardized and squared standardized residuals, respectively. IGARCH model could not be estimated for CNX IT, BSE 100, BSE 200 and CNX 500.

Table 6.3: Estimates of FIGARCH Model

Index Returns	Mean	C	ϕ	β	*d*	Q(20)	$Q^2(20)$
CNX Nifty	0.0013	0.0000		0.2820	0.436*	64.10	16.86
	(0.000)	(0.102)		(0.000)	(0.000)	(0.000)	(0.662)
CNX Nifty Junior	0.0016	0.0000		0.2849	0.492*	124.32	27.79
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.114)
CNX Defty	0.0014	0.0000		0.240	0.403*	60.014	15.83
	(0.000)	(0.218)		(0.000)	(0.000)	(0.000)	(0.727)
CNX IT	-	-	-	-	-	-	-
BSE Sensex	0.0013	0.0000		0.311	0.446*	64.14	26.25
	(0.000)	(0.2168)		(0.000)	(0.000)	(0.000)	(0.159)
BSE 100	-	-	-	-	-	-	-
BSE 200	-	-	-	-	-	-	-
CNX 500	-	-	-	-	-	-	-
CNX Bank Nifty	0.0011	0.0000	-	0.2210	0.361*	68.76	17.33
	(0.002)	(0.386)		(0.000)	(0.000)	(0.000)	(0.631)
BSE 500	0.002	0.0000	-	0.112	0.562*	78.54	2.49
	(0.000)	(0.000)		(0.152)	(0.000)	(0.000)	(0.999)
CNX 100	0.0018	0.0000	-	0.570	0.721*	42.02	31.35
	(0.000)	(0.000)		(0.000)	(0.000)	(0.003)	(0.051)
CNX Infrastructure	0.0022	0.0000	-	0.5122	0.693*	54.65	35.51
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.017)
BSE Mid Cap	0.0021	0.0000	-	0.2717	0.572*	77.30	27.99
	(0.000)	(0.007)		(0.002)	(0.000)	(0.000)	(0.111)
BSE Small Cap	0.0022	0.0000	-	0.1149	0.410*	95.80	28.47
	(0.000)	(0.309)		(0.196)	(0.000)	(0.000)	(0.109)

Note: The table reports the Quasi maximum likelihood estimates (QMLE) for FIGARCH (*p,q*) model for the stock return on the various indices of NSE and BSE. C denotes constant in variance equation, β represents GARCH (lagged variance) parameter, ϕ denotes autoregressive parameter in conditional variance quation. The values in the parentheses represent significance level. *d* represents estimated fractional difference parameter. Q (20) and $Q^2(20)$ refer to the Ljung-Box portmanteau tests for up to 20^{th} order serial correlation in the standardized and squared standardized residuals, respectively. FIGARCH model could not be estimated for CNX IT BSE 100, BSE 200 and CNX 500.

SUMMARY, MAJOR FINDINGS AND IMPLICATIONS OF THE STUDY

Summary and Major Findings:

The past decade has witnessed introduction of important financial sector reforms aimed at a vibrant capital market. With a phenomenal growth of Indian equity market, and its growing importance in the economy as indicated by percentage of market capitalization and increasing integration of Indian economy with global economy, India has emerged as one of the important destination for investment. Drastic market microstructure changes aimed at transparent, fair and efficient market are set in. In the light of these changes, it is felt imperative to study the returns behaviour in Indian equity market.

There are various schools of thought which explain behaviour of stock returns. The efficient market theory or hypothesis is one of the important theories based on rational expectation and no-trade argument of neoclassical finance. The main architect of the theory is Eugene Fama who provided strong theoretical foundations and also a framework to test the market efficiency. In an efficient market, prices quickly absorb new information and reflect all available information and this kind of price processing mechanism does not provide extra normal returns. Facilitation of conducive investment climate and optimal allocation of capital, which are the vital functions of market, would be affected adversely in an inefficient market. Testing market efficiency, therefore, assumes importance because of its theoretical importance and practical implications.

A large body of research produced in the last three decade itself reflects importance of an efficient market. Various techniques are employed in the empirical studies to test different forms of market efficiency. Random walk hypothesis is considered as one of the effective and convenient way to test weak form of efficiency. In an efficient market, returns are expected to respond randomly to new information and therefore it is not possible to predict futures returns based on past memory of prices. Various techniques are employed in the empirical works to assess randomness of stock returns. There has been a paradigm shift in post 1987 studies which reported non-linear dynamics in stock returns. The conventional tests of market efficiency found to be incapable to capture such dynamics. Concomitant to this, long memory time series properties have gained attention in last one and half decade.

In light of above, the main purpose of the present study is to examine the returns behaviour in Indian equity market in the changed market environment. It primarily focuses on weak form of efficiency. To test linear and non-linear dependence in stock returns different tests are carried out in this study. Furthermore, the study attempted to detect long memory in mean and volatility returns. The data used in the study consists of daily stock returns of two premier stock exchanges namely, National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). Eight indices including three sectoral indices from NSE and six indices from BSE are selected. The study differs from previous studies in application of sophisticated tests, using new and comprehensive data and addressing issues which are seldom discussed in the context of Indian equity market.

The present study empirically tested whether stock returns in NSE and BSE follow a random walk. Towards this end, data on major indices during the period January 1997-Maarch 2009 are analyzed using both parametric and non-parametric tests, some of which are not employed in previous studies in India. Results from parametric tests though offer mixed evidences, the weight of the evidences suggest rejection of random walk hypothesis in case of smaller stock indices with lower market capitalization and liquidity. Indices having higher market capitalization and liquidity appear to follow a random walk. This is further supported by results of non-parametric ranks and signs based variance ratio test. It is found that highly liquid indices provided weaker evidences against RWH. Non-parametric tests, which are considered to be appropriate when returns are non-normal, show rejection of the hypothesis that increments are independent and identically distributed (i.i.d) for all selected indices irrespective of their market capitalization or liquidity.

Non-linear dependence in returns directly contrasts the efficient market hypothesis (EMH). It is because of the fact that non-linear dependence indicates potential for predictability. The conventional tests cannot capture such dependence. Given the fact that there has not been much empirical work in this context, the present study applied a set of non-linearity tests which have different power against different classes of non-linear process, to uncover non-linear dependence in stock returns of selected indices. The test results provide strong evidence of non-linear dependence in stock returns. However, the windowed test procedure applied in the study shows a non-linear structure that is not consistent throughout the sample period and confined to a few pockets thus suggesting episodic non-linear dependence surrounded by long periods of pure noise. The study further probes the issue by exploring the events that occurred during the sample period where non-linear evidences are strong. It is found that both negative and positive events possibly may have generated non-linear dependence. However, significant non-linear periods are largely associated with 'bad' events.

The mean-reversion hypothesis is tested as an alternative explanation of stock returns to random walk behaviour. Along with conventional unit root tests, Zivot-Andrews single break Lee-Strazicich two break tests are employed to treat structural breaks which cannot be captured by unit root tests. The results of unit root tests provide evidence of mean reverting tendency in stock returns across all the chosen indices. The Zivot-Andrews single break test also indicates mean-reversion. Furthermore, the results from Lee-Strazicich two breaks test suggest rejection of null of unit root clearly indicating trend stationary process in 12 of the 14 indices considered for the testing. The study identified the events associated with significant structural break dates as indicated by tests. These events are, dot.com bubble burst and global economic recession in the year 2000, bad monsoon and border tensions in 2003, and international oil shocks and volatile exchange rates, sub-prime crisis and global economic meltdown in 2007 and 2008 and political uncertainties.

The issue of long memory is examined in the present study. To detect long memory in mean returns, Geweke and Porter-Hudak semiparametric, Robsion's Gaussian semiparametric and Andrews and Guggenberger's log periodogram tests are carried out. The results of former two tests provide mixed evidences, while the latter test results largely indicate long-range dependence. The anti-persistence evidences observed in index returns are not consistent. The findings by and large indicate long memory in mean returns of most of the indices. The proposition that smaller indices are largely characterized by long memory than larger indices has not been supported by the results.

In the same fashion, the present study endeavoured to detect long memory in volatility, which has important theoretical and policy implications as well. Fractionally integrated generalized autoregressive conditional heterosceasticity (FIGARCH) model of Baillie *et al* (1996) has been applied to detect long memory in variance. The model estimates indicate strong evidence of long memory in volatility with few exceptions, thus suggesting predictable components in volatility. It is also found in the present study that the FIGARCH model better describes the persistence of volatility than the conventional ARCH class model such as GARCH.

Implications of the Study

To conclude, time series econometric techniques applied in the study by and large suggest rejection of random walk behaviour in Indian equity market. This implies that Indian equity market is not weak form efficient. The results indicate no significant difference in behaviour of index returns between NSE and BSE. Nevertheless, the stock indices having higher liquidity and market capitalization prove to be less inefficient than small indices on both the exchanges. Furthermore, the small indices with less liquidity appear to be more vulnerable to external shocks. Sector wise, there has not been much difference. Though indices of information technology and banking sectors provide weak evidences against random walk, the returns behaviour of these indices seems to be external driven. In other words, the returns behaviour is subject to events such as the turmoil in exchange rates and sub-prime crisis. Such shocks appear to have altered the time series properties of the underlying returns. Further probing into the secotral efficiency with a still broader set of sectoral indices is warranted.

The study indicates presence of non-linear dependence. In addition, the presence of long memory both in mean returns and volatility returns is detected. The presence of non-linearity and long memory violates weak form efficient hypothesis in the context of Indian equity market. The episodic presence of non-linear dependence implies that certain events induce such non-linear dependence. Further, the long memory process indicates slow mean reverting tendency in stock returns. The episodic dependence in returns indicates that investors take time to learn about shock and adjust their trading strategies. The rejection of random walk at long horizon (by certain tests) implies that the information in short-horizon is not instantly reflected in returns and thus provides opportunity for excess returns to those who have access to this information. Later, as time horizon increases, information gets reflected on returns leading towards market efficiency. The evidence of long memory both in mean and volatility suggest that using linear modeling of would results in misleading inferences. The evidence of long memory suggest proper filtering for derivative pricing and risk management models.

In view of the above discussion, some policy implications can be mentioned. Existence of excess of returns in short horizons of investment calls for proper dissemination of information to the participants. Further, to improve the performance of small indices having lesser liquidity, it is important to improve liquidity. This can be achieved by encouraging retail trading in the market. The external events have always created panic in the Indian equity market. Whenever there were some shocks, it was found that there was net outflow of FIIs. This calls for an appropriate regulation of external sector and FIIs and further disclosure from FIIs.

The limitations of the study highlight scope for further research. The present study is based on aggregate and sectoral indices only and confined to daily data. The study might be extended further by using high frequency data such as tick-by-tick and also by repeating the same at the level of individual stocks. This will be helpful in understanding dynamics of market further and also would throw light on episodic dependence and speed of price adjustment. Although the study indicated stronger rejection of market efficiency and vulnerability to external shocks for less liquid indices, model explaining interaction between market microstructure variables and market efficiency indicators is to be explored. Lastly, the sources of long memory and also volatility shifts in long memory volatility should be further investigated and application of Wavelet methods may give new insights into issues of long memory in stock returns.

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