Financial Market Efficiency: An Empirical Examination of the Indian Stock Market

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*I hereby affirm that the work for this dissertation, **'Financial Market Efficiency: An Empirical Examination of the Indian Stock Market'** being submitted as a part of the requirements of the M. Phil Programme in Applied Economics of the Jawaharlal Nehru University, was carried out entirely by myself. I also affirm that it was not part of any other programme of study and has not been submitted to any other University for the award of any degree.*

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Certified that this study is the bona fide work of Anand S, carried out under our supervision at the Centre for Development Studies.

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Dedicated to

My Father, who (still) beats me at badminton et al

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Abstract

Information efficiency of the stock market prices is necessary for the capital market to be an efficient resource allocator. When prices reflect information quickly and accurately, it rules out the possibility of generating excess returns by trading on available information. Then the market is efficient according to the 'Efficient Markets Hypothesis'.

Against this theoretical backdrop the behaviour of S&P CNX Nifty for the period January 1991 to October 2008 is examined here. The study proceeded by first identifying periods of structural changes in the market, and then examining the return generating process across these periods. The insights from these were used in analysing weak-form efficiency. The persistence of anomalies to market efficiency was also tested across the periods of structural changes. Finally, the case of semi-strong efficiency was examined by conducting an event study on monetary policy announcements and its impact on the stock market behaviour.

Applying Bai-Perron test for multiple structural changes, four breaks in the series were identified. The break points correspond to December 1994, July 1999, June 2003 and January 2006. On examining the statistical distribution of returns for this time period it was found that the return distribution is better approximated by a stable Paretian distribution. This class of distribution has the property of infinite variance, thus making any measurement using sample variance misleading. Therefore, nonparametric statistics is used in all our analysis.

Weak form efficiency was tested across the periods of structural breaks using runs test. It was found that markets have become weak form efficient after the third structural break, corresponding to June 2003. Weak form efficiency was also examined by testing for the presence of seasonality in returns, which makes returns predictable. Testing for consistency in the order of returns across the periods of structural breaks using rank correlation coefficient, we reject the presence of seasonality of returns in India.

Semi-strong efficiency of the market with respect to monetary policy announcements in India was then examined. The market behaviour during the three-day event window comprising of the day before the announcement, the day of announcement and the day after it, was examined. The periods adhering to weak form efficiency was particularly studied. Various nonparametric tests were developed to see whether there is systematic

component in the market behaviour across events. The study find no systematic, consistent impact of monetary policy announcements immediately affecting the Indian stock market.

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Chapter 1

Introduction

There is a view that the stock market reflects investors attempts to forecast economic trends [1]. There is also a saying that the stock market has forecast ten of the last six recessions (Fischer and Merton, 1984). But 2008 economic crisis orignating from sub–prime lending in the U.S housing markets has left shaken not only the financial markets across the world, but also the real sector [2]. It is said that one needs to understand efficient markets hypothesis not because it is universally true, but because it leads you to ask the right questions (Brealy and Myers, 2003). In the context of threatened jobs, lost savings and eroded wealth and confidence, we probe this question – How efficient are our markets? This is the question we try to answer through this research.

This chapter serves as an introduction to this research while introducing the underlying concepts and theory. Section§1.1 introduces the concept of financial market efficiency. Section§1.2 provides a formal derivation of the theory of the efficient markets. Section§1.3 discusses the empirical literature from India. Section§1.4 lists out the research objectives. Section§1.5 details about the data and methodology used, and the chapter schema for the rest of the thesis can be found in section§1.6.

[1]"The fact that movements in stock prices foretell major cycles in business activity is, thus, only evidence that investors' forecasts are better than random guesses" (Bosworth, Hymans, and Modigliani, 1975)

[2]Wray (2008), Bordo (2008), Crotty (2008), Gorton (2009) Gorton (2008)

1.1 Posing the Problem

Stock market plays an important role in the growth process of an economy. Its primary role is of an institution facilitating capital mobilization. By acting as an additional channel for mobilising savings, it can ensure a more transparent corporate control and managerial action. In the process it facilitates productivity of investment through market allocation of capital (Biswal and Kamaiah, 2001).

Stock market directly influences the allocation of capital resources in an economy. It directly influences portfolio management, which influences the allocation or reallocation of resources among the outstanding securities; and the primary market allocates resources in the economy influenced by the prices established on secondary markets (Reddy, 1998). Given indirect costs (asymmetric information and related costs) involved, the prices in the secondary market perform the role of information signals and direct the allocation of resources. Therefore, information efficiency is a precondition for achieving allocation efficiency.

A market is said to be efficient if it fully and correctly reflects all relevant information in determining asset prices. This makes it impossible to outperform the market using any publicized information. When these two conditions hold, the market is said to be efficient according to the Efficient Markets Doctrine. Its origins can be traced back to the Bachelior's 1900 doctoral dissertation — "The Theory of Speculation". He proposed then what we now call the 'Random Walk' of stock market prices and argued that there is no useful information contained in historical price movements of securities. However, the interest in it was revived only in the sixties by the works of Paul Sameulson, Eugene Fama, Jensen and others. The story goes that Bachelior's work received little attention until Samuelson 'rediscovered' it. Its english translation was later published in Cootner's anthology (Cootner, 1964) of related works. Today, the concept of Efficient Markets Hypothesis is spoken in synonymous with the works of Fama (1965, 1966, 1970, 1988, 1991).

Information efficiency of a market refers to the ability of a market to process, analyze and reflect information fully and instantly in the market prices. From this it follows that, current market prices of financial assets embody rationally all the known information about prospective returns from the asset. Price changes are observed due to two factors. Firstly, prices change as a result of fresh information relating to the assets' prospective returns. As successive bits of new information arise independently and randomly, the successive price changes will also be independent and random. Secondly, it is possible that the current price deviate from the correct price by the action of uninformed traders which create 'noise'. Noise arises due to the uncertainty or disagreement between the traders concerning the intrinsic value of the asset, since each individual's valuation of this intrinsic value is independent of each other . But such disequilibrium created by the noisy traders is expected to be white noise [3] and simply temporary aberrations. This is the Bachelior-Osborne hypothesis that the asset prices follow a random walk. The theory of random walk of stock prices implies that (a) successive price changes are independent, and (b) price changes follow a probability distribution.

Black (1986) illustrates how 'noise' influences prices and trading. According to him noise makes financial trading possible, but also makes them imperfect. He contrasts noise with information. Noise trading is trading on noise as if it were information. Noise trading makes prices noisy and therefore the price of a stock reflects both the information and noise the respective traders trade on. When there are many noise traders in the market it pays for trading with information. The noise in the market will be cumulative, like "a drunk tends to wander farther and farther from his starting point" (Black, 1986, p. 532). This is, but, offset by the action of information traders. As the prices gets farther from its value, the more aggressive the information traders become. This makes the prices to move back toward its value over time.

With regard to independence of price changes, Fama (1965) points

[3]White noise implies a mean-reverting process with zero mean, constant variance and no-autocorrelation. A time series is called a stationary process when its mean, variance and covariance are all constant independent of time. A white noise process is a stationary process, but not vice versa.

out that dependence that is important for a statistician need not be important for an investor and vice-versa. He argues that the assumption that prices are independent is valid as long as the actual dependence of the series of price change is not sufficient to allow the past history of the series to be used to predict the future in such a way that he can make expected returns beyond the naive buy and hold strategy. Also, it is possible that there could be dependence in the noise generating process (follow opinion leaders), or information generating process. Such dependence can create asset price bubbles. But, if there are enough sophisticated players the bubbles burst before they start. Their actions can neutralize the dependence in noise generating process, and successive price changes will be independent.

These are the foundations of Efficient Markets Hypothesis (EMH), which posits that current prices reflect all available information, and price changes are independent; such that it is futile to engage in price forecasts or in any trading strategy based on available information with the expectation of fetching excess returns. Thus, three points are emphasized in Efficient Markets doctrine, namely (i) the importance of the information set; (ii) the ability to exploit this information in a trading strategy; and finally (iii) that the yardstick for testing if the EMH holds.

Based on information set , EMH literature suggests three forms of market efficiency (Fama, 1970). Excess returns cannot be achieved with investment strategies based on historical prices. The asset prices will not have serial dependence since future price movements are determined entirely by unexpected price movements and therefore will be random. If this holds true then the market is said to be weak form efficient. If no excess returns can be made by trading on published information, then that market is said to be semi-strong efficient. Finally, if the asset price reflects all information public and private, such that even insider information cannot provide you with excess returns. Then the market is Strong-form efficient.

The implications of Efficient Markets Hypothesis is far fetched and has important macroeconomic and policy implications. For example, understanding the efficiency of the financial markets is important in assessing the macroeconomic effects of further liberalization of the financial sector. For instance, the case of free capital mobility is crucially contingent on the efficient market hypothesis (Nachane, 2007). It has macroeconomic implications particularly when current account deficit in India is increasingly financed with capital inflows from global financial markets. The volatility in forex markets (when the actual trading strategies of forex traders are in systemic violation of rational market behavior) can produce violent swings in important asset prices such as real estate, equities and the exchange rate itself.

EMH has macroeconomic implications in terms of banking practices and quality of saving and investment instruments as well. An inefficient market can create asset bubbles and crashes not backed by fundamentals, eroding the asset value and confidence in the markets. Inefficient markets run the danger of converting a currency crisis to a banking crisis. To illustrate, if competition in the banking sector is tough, the banks might get engaged in risky credit operations, but the competition might restrain them from charging risk premia. To augment their expected returns, during bullish periods the banks leverage the financial position-taking of corporate borrowers. If the trend is not backed by fundamentals, then volatility of returns sweeps away their asset base since they will not be able to adequately collateralize the loan (Nachane, 2007).

1.2 Theoretical Foundations of Efficient Markets Hypothesis

The basic argument of efficient markets hypothesis is that, a market in which prices always fully reflect available information is efficient (Fama, 1970). Agents in the market form expectations based on the current information set ϕ_t, and if markets are sufficiently competitive then investors cannot expect to achieve superior profits from their investment strategies based on their information set. This is because "in competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen" (Samuelson, 1965).

The prices are expected to follow a 'martingale model' [4] which implies that all currently available information is embodied in the current prices (Fama, 1970; Bailey, 2005). This implies that[5]

$$E(p_{t+1}|\phi_t) = p_t \tag{1.1}$$

The above equation states that the expected price for the next period (p_{t+1}), based on the current information set (ϕ_t) will be equal to the current price. This is because the investors are assumed to be rational agents, who use all available information to arrive at their decision. And, the information that influences their decision gets reflected in the current prices. The wisdom contained in equation 1.1 can be best found in these words, which is from the man who first thought about it probably —"Past, present and even discounted future events are reflected in market price, but often shows no apparent relation to each other" (Bachelier, 1900).

From equation 1.1 we can see that

$$E[(p_{t+1} - p_t)|\phi_t] = 0 \tag{1.2}$$

Instead it is safe to assume a sub–martingale model, where

$$E(p_{t+1}|\phi_t) \geq p_t \tag{1.3}$$

Or, we can think of this process as being generated by

$$E(p_{t+1}|\phi_t) = (1 + \mu)p_t \tag{1.4}$$

Rearranging the equation, we can see that

$$\mu = \frac{E(p_{t+1}|\phi_t) - p_t}{p_t} \tag{1.5}$$

[4] A *martingale* can be thought of as stochastic or random process (P_t) which satisfies the following condition $E[P_{t+1}|P_t, p_{t-1}, ...] = P_t$, or equivalently, $E[P_{t+1} - P_t|P_t, p_{t-1}, ...] = 0$. (Campbell, Lo, and MacKinlay, 1997).

[5] The discussion on martingales is based on Bailey (2005, p. 57)

Here, μ is a constant and can be interpreted as the *expected* rate of return. Now, we define rate of return as

$$r_{t+1} = \frac{p_{t+1} - p_t}{p_t} \tag{1.6}$$

By introducing the expectations operator, we get

$$E(r_{t+1}|\phi_t) = \frac{E(p_{t+1}|\phi_t) - p_t}{p_t} = \mu \tag{1.7}$$

Using the law of iterated expectations, we can write

$$E(r_{t+1}|\phi_t) = E(r_{t+1}) = \mu \tag{1.8}$$

The expected rate of return conditional on current information equals the unconditional expectations of the rate of return (Bailey, 2005). This implies that currently available information cannot be used in predicting future returns.

Since, $r_t \in \phi_t$

$$E(r_{t+1}|r_t) = \mu \tag{1.9}$$

Or,

$$E(r_{t+k}|r_t) = \mu; \forall k \geq 1 \tag{1.10}$$

More generally, since the information set can contain historical data i.e., current and past prices and returns

$$E(r_{t+k}|r_t, r_{t-1} \ldots) = \mu \tag{1.11}$$

Therefore, we can have

$$r_{t+1} = \mu + \epsilon_{t+1} \tag{1.12}$$

Where,

$$E(\epsilon_{t+1}|\phi_t) = 0 \tag{1.13}$$

An issue of great interest in EMH is excess returns. Fama (1970) defines excess returns as

$$x_{t+1} = p_{t+1} - E(p_{t+1}|\phi_t), \tag{1.14}$$

then

$$E(x_{t+1}|\phi_t) = 0 \tag{1.15}$$

Excess return (x_{t+1}), is a fair game with respect to information sequence ϕ_t

From the above discussion, we can derive the following inferences about the behaviour of prices and returns. First, current return or prices provides no 'usable' or 'meaningful' information about its future. Second, from first it follows that, the current rate of return is uncorrelated with any of its past values. Third, it is not possible to make excess returns based on the current information set.

1.3 Financial Market Efficiency and India: A Review of Literature

Studies in India primarily focused at examining weak-form efficiency. One of the first of these studies was by Sharma and Kennedy (1977). They examined Bombay, London and New York stock exchanges, testing for weak-form efficiency using runs test and spectral analysis. The results were in support of efficient markets. Barua (1981) studies 20 scrips listed in the Bombay Stock Exchange (BSE) as well as Financial Express index (FE). He examined serial dependence in price changes using both parametric and non–parametric techniques, which returned with mixed results. Similar was also the case with Gupta (1985) who examined Economic Times index (ET), FE and 39 scrips in BSE. Krishnarao (1988) examining a number of scrips, tried to see whether technical trading rules or filter rules can generate 'buy' or 'sell' signals which can give excess returns, as in Fama and Blume (1966). Yalawar (1988) also examined a number of scrips using correlation tests and runs test. Both studies supported the EMH paradigm.

Table 1.1: Select Studies on Indian Financial Markets' Efficiency

	Study	Methodology	Evidence
1	Sharma and Kennedy (1977)	Runs test, spectral analysis	SupportEMH
2	Barua (1981)	Runs test, autocorrelation	Mixed Results
3	Gupta (1985)	Autocorrelation, runs test	Mixed Results
4	Krishnarao (1988)	Runs test, filter rules	Support
5	Yalawar (1988)	Rank correlation, runs test	Support
6	Choudhary (1991)	Correlation test, runs test	Reject
7	Barman and Madhusoodhan (1991)	Unit root test, variance-ratio test	Reject
8	Reddy (1998)	Runs test, ARCH, GARCH	Reject
9	Agarwal (2000)	Random walk testing	Reject
10	Thomas and Shah (2002)	Event study	Accept
11	Ahmad, Ashraf, and Ahmed (2006)	Unit-root test, GARCH, Runs test	Reject
12	Ray (2007)	Cointegration, Granger C.	Reject
13	Agrawal (2007)	Event study	Reject

Whereas Choudhary (1991) conducting similar tests rejects the hypothesis that the markets are efficient. Barman and Madhusoodhan (1991) using unit root test and variance ratio test; Reddy (1998) and Ahmad, Ashraf, and Ahmed (2006) using runs test and ARCH, GARCH models, all provides evidence in rejection of the hypothesis of efficient markets. One of the latest study in this line by Ray (2007) examines evidence for cointegration and causality of macroeconomic variables with the stock market. Of all the macroeconomic variables he examined, only index of industrial production (IIP) seems to have a little, but negligible influence over the stock markets. He rejects the efficient markets hypothesis for the Indian markets.

The studies Thomas and Shah (2002) and Agrawal (2007) is methodologically different from the other studies. The methodology pertains to *event studies* [6]. An event study, in this context, examines semi-strong or strong form efficiency by examining the market behaviour during a major event of interest. Semi-strong efficiency requires that markets react immediately to a new information and the prices capture the 'real' impact of the information on the expected future stream of earnings. A semi-strong efficient market will not continue to ride in the direction of a stale information.

Thomas and Shah (2002) examined the market behaviour for all the Union budgets from April 1979 to June 2001. The analysis was made possible by constructing a long time series data of a market price 'index' by concatenating five sets of indices for the period. Examining average cumulative returns they infer that substantial information processing takes place prior to the budget date, but with no overreaction or under-reaction prior to the budget date or immediately after it. In short, they find the market to be efficient in its semi-strong form for this information set. Agrawal (2007) conducted an event study on monetary policy announcements in India. He examines 6 announcements affecting CRR between April 2006 and July 2007. The study takes an event window of 31 days and examines the cu-

[6] After Fama (1991), tests for weak-form efficiency falls within the larger framework of *tests for predictability of returns*. Examination for semi-strong-form efficiency is now known as *event studies* and examining strong-form efficiency falls within *tests for private information*

mulative average abnormal returns (CAAR)[7] of the fifty firms constituting the market price index 'Nifty' . He shows that CAARs does not normalize after the event, indicating that market is slow in incorporating the content of the monetary policy announcements. This, he argues, is evidence for semi-stron inefficiency.

The results of major studies in India is summarised in table 1.1. Looking at it we can see that, older studies more often tend to support the hypothesis that markets are efficient. Later studies increasingly reject the efficient markets hypothesis on account of observing serial dependence or unit root. But, Fama (1965, 1991) points out that simply dependence do not reject EMH. This is because, firstly, dependence that is important from a statistical point of view might not be important from an investment point of view and vice versa (Fama, 1965). Secondly, what is of concern is whether such dependence can facilitate profitable trading strategies. Finally, prices following a martingale[8] (Samuelson, 1965) may not have the independence property of a pure random walk (Fama and Blume, 1966). In this regard Campbell, Lo, and MacKinlay (1997) points out that the concept of relative efficiency, i.e.,the efficiency of one market measured against another is a more useful concept than absolute efficiency[9]. Regarding the distributional properties of price changes, most studies do not go beyond the routine tests for normality and is often silent about its implications. Following Mandelbrot (1963), Fama (1965) shows that the return generating process is better approximated by stable Paretian distribution. This class of distribution has the property of infinite variance. Sample variance will show extremely erratic behaviour even for very large samples. Thus, statistic based on variance are meaningless or breaks-down.

[7]See section 4.1.2.

[8]See footnote 4

[9]"Few engineers would ever consider performing a statistical test to determine whether or not a given engine is perfectly efficient–such an engine exists only in the idealized frictionless world of the imagination. But measuring relative efficiency–relative to the frictionless ideal–is commonplace" (Campbell, Lo, and MacKinlay, 1997, p. 24)

1.3.1 The Literature Gap

From the discussion in the previous section we were able to see that some of the major issues regarding stock market behaviour is still under-explored to test for market efficiency. First, there is a major gap in the literature on the nature of the return distribution in India. Standard tests for efficiency such as time series tests for autocorrelation etc are highly dependent on the assumption of normality in the distribution of returns. Mandelbrot (1963) and Fama (1965) have shown that price changes could follow a Paretian distribution. This means that variance based statistics can be misleading in making inferences about market efficiency. Second, from this it follows that any test for efficiency should be devised only after taking into account the empirical distribution of the market returns. If the distribution follows paretian distribution (which it is, in the case of India), the tests should be either based on statistics conforming to this distribution or should be entirely distribution free. Third, a major assumption in the random walk model is that mean returns are constant over time. But it is quite possible that there are fairly long phases within which the mean returns would vary. This can coincide with the structural changes the market undergoes. Therefore, it is important to locate such structural changes when the mean returns could vary. Such deviations from the long term mean need not be taken as a deviation from efficiency, but is part of the markets' evolution and therefore, has to be taken into consideration. In the recent period, the Indian market has gone through significant structural changes such as improvement in operational efficiency brought out by technology; increased participation of foreign institutional investors due to the opening up the economy etc. Therefore, it is important to ask the question – how efficient is the market *today*. In short, the distribution of returns and the periods of structural changes in the market should together determine the way tests for efficiency should be carried out.

1.4 Research Objectives

Through this research we expect to 'fill' some of the 'gap' highlighted in the previous section. It will be, indeed, a curious exercise to understand the true nature of the return generating process in the Indian stock market. Market Efficiency is a dynamic process as it keeps evolving over time. If the return behaviour is one that fits the Mandelbrot-Fama hypothesis, then suitable non-parametric tests should be developed to test for efficiency. Also, only through an understanding of the structural changes this dynamic process can be analysed. That is, through our understanding of structural changes in the market and its distributional properties we expect to uncover this dynamic process. In this revised context, understanding the impact of policy announcements on the market will be a curious issue to re-look at. Budgets contain important information pertaining to taxation and government spending and fiscal support, which has huge implication on the firm's balance sheet. Equally important to a stock market is the monetary policy stance. It influence key macro variables of the economy such as the interest rates, liquidity, credit availability etc. Besides its economy wide implications, these variables tend to have a direct bearing on the stock market trading itself. Therefore, it would would be revealing to look at the impact of monetary policy announcement on the stock market behaviour using non-parametric techniques. Evidence for a systematic and consistent pattern of stock market behaviour associated with the policy announcement will form the basis of examining the facet of semi-strong efficiency. With this motivation, below we list our research objectives:

1. To identify the return generating process in the Indian stock market, and its implications on risk, return and measurement.

2. To locate major periods of structural changes through which Indian stock market has gone through.

3. To examine the dynamics of weak form efficiency of the Indian stock market.

4. To study the stock market behaviour associated with monetary policy announcements and its implications on semi-strong efficiency.

1.5 Data and Methodology

1.5.1 Data

To examine behavior and efficiency of the stock market, the daily closing price data of National Stock Exchange of India's (NSE)[10] benchmark price index 'S&P CNX Nifty' (Nifty)[11] is used. The period of analysis is January 2001 to October 2008. The purpose of using an index instead of individual share prices is because, a stock market index is expected to capture the movements of stock market as a whole. Within an index individual stock news tend to cancel out each other, and the news that is common to all the stocks stand out. A stock market price index is usually constructed as weighted average of the individual share prices included in the index, with the weights proportional to the market capitalisation [12].

S&P CNX Nifty introduced in November 3, 1995 is based on 50 largest and highly liquid stocks. In India, it is considered as the most scientific index which was constructed keeping in mind index funds and index derivatives (NSE, 2008). The S&P CNX Nifty is computed using market

[10]NSE is undoubtedly the largest stock exchange in India. NSE alone accounts for 90.34% of the total turnover on all segments in 2006-07. According to the World Federation of Exchanges Annual Report 2006, in terms of number of trades in equity shares, NSE ranks 3rd next only to NASDAQ and NYSE at the end of December 2006.The introduction of NSE's fully automated trading system for the capital market segment known as NEAT - National Exchange for Automated Trading, led to a quantum leap in the operational efficiency of securities trading in India. NSE and OTECI, was the first exchanges in India to adopt a pure demutualised governance structure where ownership, management and trading are with three different sets of people. India is the only country to have achieved demutualisation and that too in the shortest possible time(NSE, 2007a).

[11]S&P stands for the endorsement of the index by the US based Standard & Poor's Financial Information Services; and CNX stands for CRISIL NSE Index. The S&P CNX Nifty is owned and operated by IISL, a joint venture by NSE and CRISIL to focus on index management. IISL was launched in 1998 becoming India's first specialised company focusing on index as a core product (www.nseindia.com)

[12]Market capitalisation is the product of market price and the total number of outstanding shares of the company.

capitalisation weighted method wherein the level of the Index reflects the total market value of all the stocks in the Index relative to the base period November 3,1995. Base market capital of the Index is the aggregate market capitalisation of each scrip in the Index during the base period. The market capitalisation during the base period is equated to an Index value of 1000, known as the base Index value. Current market capital of the Index is the aggregate market capitalisation of each scrip in the Index during the current period. The current price of each stock is multiplied by the number of shares outstanding to give the aggregate current market cap of the Index. The general index[13] formula calculation is as follows:

$$Indexvalue = \frac{CurrentMarketCapital}{BaseMarketCapital} * BaseIndexValue \tag{1.16}$$

All companies to be included in the index should have a market capitalisation of Rs. 5 billion or more. A company entering the index should have double the market capitalisation of the company leaving the index. All securities should fully satisfy the required execution on 90% of the trading days at an impact cost of less than 0.75% in the last six months.[14]

The data is freely available at RBI data warehouse and NSE's website. Though Nifty started trading only by the end of 1995, data from 1991 is available which is the indice's back-computed data, computed based on historical prices and market capitalisation.

Of late the importance of an index is much more than just a market tracker. It has direct financial applications in the form of index funds and index derivatives, and as a benchmark for measuring the performance of the fund manager. An index fund is a mutual fund investment scheme that invests in securities of the target index in the same proportion or weightage. Thus it emphasis at broad diversification and low portfolio trading activity. It is lauded for its passive investment approach, a direct outcome and applicaton of EMH, where no attempt is made at 'active' money man-

[13]Nifty is called an event–driven index because price changes in any of the securities will lead to a change in the index. The weightages are not fixed and they change with the stock price movements.

[14]NSE (2007a,b, 2008), www.nseindia.com

agement or other tactics to outpace the index. Their purpose is to provide returns that is commensurate with the benchmark index.

Nifty BeES introduced by *Benchmark*, an asset management company, on 8 January 2002 is the first ETF in India. It is traded in the capital segment of NSE, with each unit priced at one–by–tenth of S&P CNX Nifty's value. It can be traded like a share through any Nifty terminal at prices available on the screen

1.5.2 Methodology

Our analysis is based on daily returns data. Returns are measured as changes in log of closing prices.

$$r_{t+1} = logP_{t+1} - logP_t \tag{1.17}$$

Where, r_{t+1} is the return from security. P_{t+1} is the closing prices of the security on day t+1 and P_t is the closing price on day t. The advantage of using change in log prices is manifold. First, it is the yield of holding the security for that day with continuous compounding. Second, taking log neutralizes the price effect since the variability of price changes will be an increasing function of the price level. Third, for changes less than ± 15 per cent the change in the log price is very close to the percentage price change (Fama, 1965).

The research began by examining the time series data to locate for structural changes. Using Bai-Perron's test for endogeneous multiple structural changes (Bai and Perron, 1998), we identified four structural changes in the series. The distribution of returns through these periods was examined to identify the theoretical distribution. On finding the distribution to follow a stable Paretian distribution, it was decided to use only nonparametric techniques. Weak form efficiency was tested across the periods of structural breaks using the nonparametric technique of runs test. It revealed that market turned to become weak-form efficient since the structural break corresponding to 2003. Weak form efficiency was also examined by testing for the presence of any common anomalies such as seasonality of returns. Finally, an event study was carried out for monetary policy announcements. The period having weak form efficiency was tested using various distribution-free techniques to see whether there is any systematic and consistent behaviour across events.

1.6 Chapter Scheme

The rest of the thesis is organized as follows.

Chapter§2 is an overall examination of the behaviour and performance of the stock market prices. It identifies structural break and examines the distribution of the return generating process Chapter§3 is concerned with examining weak–form efficiency of the market. It continues into Chapter§3.3 investigating whether predictability of the market in terms of seasonality exists. Chapter§4 conducts tests for semi–strong efficiency, by examining the impact of monetary policy announcements on the market behavior. Finally, we conclude with Chapter§5.

Chapter 2

Stock Market Prices: Structural Break & Distribution

This chapter acts as a springboard for the rest of the thesis to follow. It identifies structural breaks in Nifty and examines its return generating process. The chapter is arranged as follows: Section§2.1 examines the tests for structural break of the series. Section§2.2 discusses the features of the return distribution. A summary of the findings of this chapter is provided in section§2.3.

2.1 Structural Break Analysis

We make use of Bai and Perron (1998) method for estimating structural break in the nifty series. This method has been applied in the Indian context by Balakrishnan and Parameswaran (2007) and Pushpangadan and Parameswaran (2003), to test for structural breaks in the growth rates of the econmy. Conventional approach to structural breaks has been to perform Chow tests, which is to perform tests for statistically significant differences in parameters across the periods suspected of a break. The basis of a Chow–test, i.e., the break–dates that needs to be confirmed by a Chow–test, can come from two ways. One is to identify break–dates based on some known feature of the data such as an inflexion point or based on the occurance of an exogenous event (Balakrishnan and Parameswaran, 2007). The limitations pointed out for this method is that, for the first ap-

Figure 2.1: Log Closing Prices of Nifty from '91 to '08

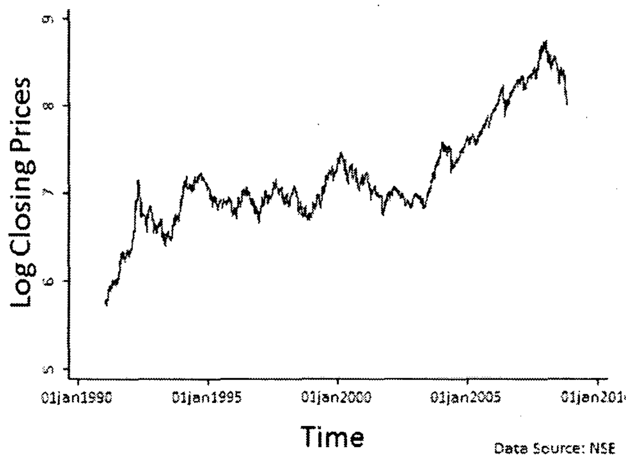


Figure 2.2: Daily returns for Nifty from '91 to '08

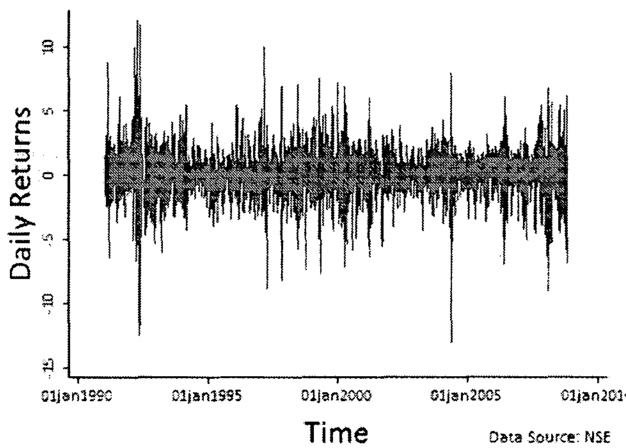


Figure 2.3: Daily returns for Nifty from '91 to '08: Scatter

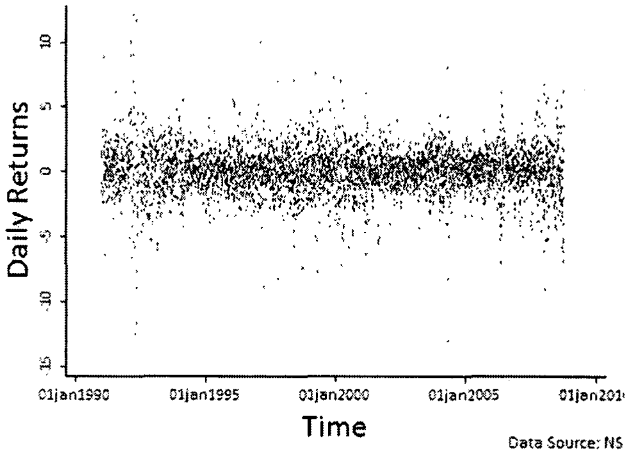


Figure 2.4: Average of daily returns: Yearly

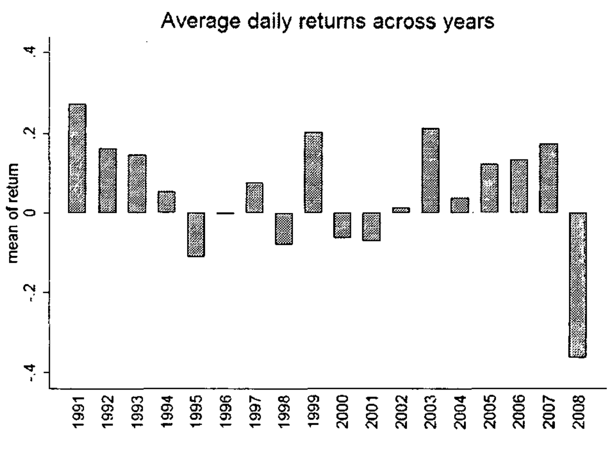


Table 2.1: Summary Statistic of Daily Returns: Across Years[a]

Year	Mean	Std Dev	Year	Mean	Std Dev
1991	.27	1.70	2000	-.06	2.00
1992	.16	3.31	2001	-.07	1.63
1993	.15	1.75	2002	.01	1.06
1994	.05	1.40	2003	.21	1.23
1995	-.11	1.24	2004	.04	1.77
1996	-.004	1.52	2005	.12	1.11
1997	.07	1.80	2006	.13	1.65
1998	-.08	1.78	2007	.18	1.60
1999	.20	1.84	2008	-.37	2.53

[a] Data Source: NSE

proach the choice of the date will be correlated with the data and the Chow–test is likely to validate a break-point when none exists. And, in the second approach it assumes that the event had an impact on the parameters of the model and it is the only causal factor at that point of time (Balakrishnan and Parameswaran, 2007). Another limitation is that it can be used to estimate only one break point at a time.

The Bai–Perron method allows for simultaneous estimation of unknown multiple breaks. The break–dates are estimated as global minimizers of the sum of squared residuals from on OLS regression of the multiple regression model using a dynamic programming algorithm (Balakrishnan and Parameswaran, 2007).

The method in Bai and Perron (1998) is as follows.

Consider the following multiple linear regression with m breaks (This gives us m+1 regimes).

$$Y_t = x_t^{'}\beta + z_t^{'}\delta_j + u_t, \tag{2.1}$$

Where $t = T_{j-1} + 1, ..., T_j$. For $j = 1, ..., m + 1$.

We denote $T_0 = 0$ and $T_{m+1} = T$. The indices $(T_1, ..., T_m)$ or the breakpoints are treated as unknowns.

For each m-partition $(T_1, ..., T_m)$ denoted $\{T_j\}$, the associated least–squares estimates of β and δ_j are obtained by minimizing the sum of squared residuals.

$$\sum_{i=1}^{m+1} \sum_{t=T_{i-1}-1}^{T_i} [y_t - x_t^{'}\beta - z_t^{'}\delta_i]^2 \tag{2.2}$$

Let $\hat{\beta}(\{T_j\})$ and $\hat{\delta}(\{T_j\})$ denote the resulting estimates. Substituting them in the objective function and denoting the resulting sum of squared residuals as $S_T(T_1, ..., T_m)$, the estimated break–points $(\hat{T}_1, ..., \hat{T}_m)$ are such that

$$(\hat{T}_1, ..., \hat{T}_m) = argmin_{(T_1,...,T_m)} S_T(T_1, ..., T_m) \tag{2.3}$$

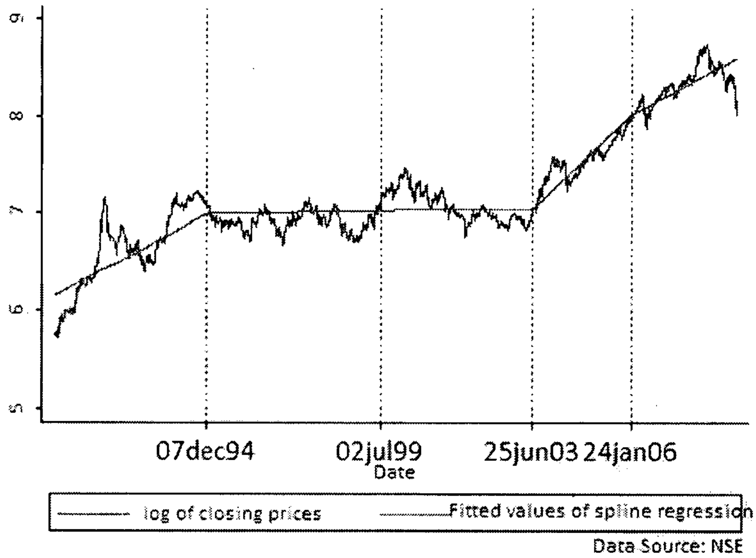
where the minimization is taken over all possible partitions $(T_1, ..., T_m)$ such that $T_i - T_{i-1} \geq q$. Note that q is the minimum length assigned to a segment and T_i is the break–point. The proceduer considers all possible combination of segments and selects the partition that minimizes the sum of squared residuals. The least–squares estimators of the break–points are the global minima of the sum of squared residuals of the objective function in §2.1. (Bai and Perron, 1998). [1]

This procedure returned 4 break–points in the Nifty series from 1991 to 2008 (see figure §2.5). This would imply that there are 5 parts or regimes to the series. They are

1. Regime 1: 02Jan91 to 07Dec94
2. Regime 2: 07Dec94 to 02Jul99
3. Regime 3: 02Jul99 to 25Jun03
4. Regime 4: 25Jun03 to 24Jan06
5. Regime 5: 24Jan06 to 23Oct08

[1]The *strucchange* package in the 'R' computing environment, provides a platform for undertaking tests for structural breaks. For details on performing it see Zeileis, Leisch, Hornik, and Kleiber (2005).

Figure 2.5: Structural Breaks in the Nifty series



With m breaks, there are m+1 regimes. We have 4 break–points, therefore 4+1 regimes. Now let us take a look at Nifty's performance across these regime. See Table §2.2.

The average daily returns has been highest during the first regime of January 1991 to December 1994 at 0.16%, which is more than three times higher than the long term mean of 0.05%. The same period also had the highest volatility in terms of standard deviation (2.138). The 2nd regime of December 1994 to July 1999 had the lowest average daily returns. The third regime of June 2003 to January 2006 had the lowest volatility, with a standard devitation of 1.44.

From Figure §2.5 we can see that that, though the long term trend was an increasing one for the first regime, it had two bull phases and a bearish phase in between. The period also saw stock market scams, which is reflected in this bearish phase. The second bull run retraced the previous high and gained resistance[2] at that level throughout the next

[2]In the 'technical analysis' jargon, *support* is the price level through which a stock or market seldom falls and *resistance* is the price level that a stock market seldom surpasses. 'Support' represents the level at which buying pressure is strong enough to absorb and

Table 2.2: Performance across structural breaks[a]

Break	Regime	Period	Mean	StdDev
0	1	02Jan91 to 07Dec94	0.160	2.13
1	2	07Dec94 to 02Jul99	0.0002	1.66
2	3	02Jul99 to 25Jun03	-0.008	1.55
3	4	25Jun03 to 24Jan06	0.148	1.45
4	5	24Jan06 to 23Oct08	0.002	1.96
		02Jan91 to 23Oct08	0.052	1.758

[a] Own computation. Source data from NSE

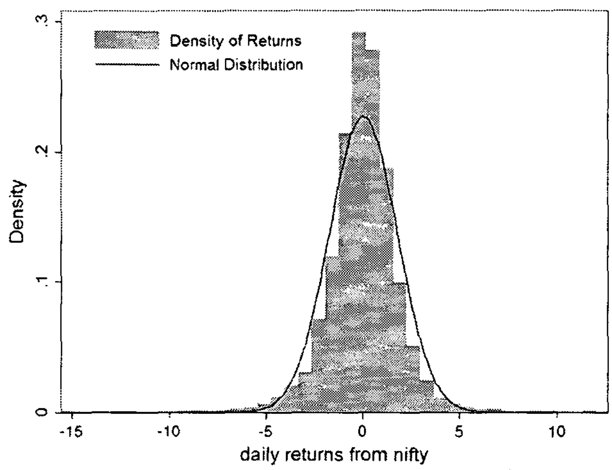
regime as well. In the second regime, the market gained support at 6.6 (log prices) and maintained it throughout. It tested the previous resistance during the bull–run beginning from the start of 1999 and which continued till February 2000, when it reached a new high of 7.47. But, the market couldn't sustain this level and soon trended downwards until it stabilised in the previous support and resistance levels. The third regime was fairly an up–trending one, except for a brief bear–phase during April – June 2004, immediately after the market testing for new resistance level at 7.6. After which, it continued to trend upwards with higher highs and higher lows. In the fourth regime, the market rose from 8 in June 2006 to 8.74 January 2008. Then it nosedived, until it retracted back to the 2006 levels.

2.2 Analysis of Distribution of Returns

It is important to analyze the distribution of return as it has direct relationship with the riskiness of the investment and in the formation of expec-

overcome the selling pressure. At price support levels buyers step into the market mopping up the imbalance between supply (sellers) and demand (buyers) and when this happens the price will halt its decline and will potentially rise. 'Resistance' is the opposite of support and is the level at which the volume of selling (supply) outweighs the volume of buying (demand). These mini-levels can change frequently but over time a clear pattern emerges and firm levels become established. (www.investorintelligence.com)

Figure 2.6: Histogram of Daily Returns



tations about returns itself. Besides, statistical inference is based on the assumptions about the distribution.

The Bachelior–Osborne model of the random walk of security prices assume that price changes are independent, identically distributed random variables; transactions are fairly uniformly spread over time; and the distribution of price changes from transaction to transaction has finite variance. If the number of transaction is very large, then the price changes will be sums of many independent variables. Under these conditions, according to the central limit theorem price changes will have normal distribution (Fama, 1965).

The easiest way to analyse the distribution of returns is examine its frequency distribution. As can be seen from Fig §2.6 and Fig §2.7, the distribution is much peaked at the center than expected of a normal distribution. Box–plot is also a convenient tool in analysis of distribution. The box shows the inter–quartile range. The median is the line inside the box. The size of the box shows the mid–spread or middle 50% of the values, which is the difference between the 25th and 75th percentile. The size of the box tells you the spread. The line inside the box is the median. The whiskers extend to at most 1.5 times the box width. The points outside

Figure 2.7: Density of Returns with Normal Distribution

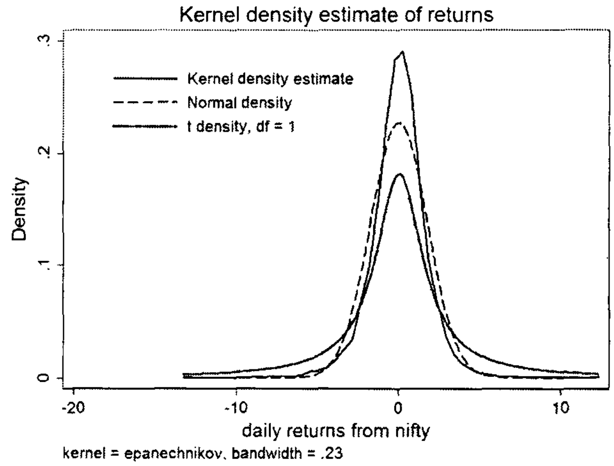


Figure 2.8: Box plot of Daily Returns

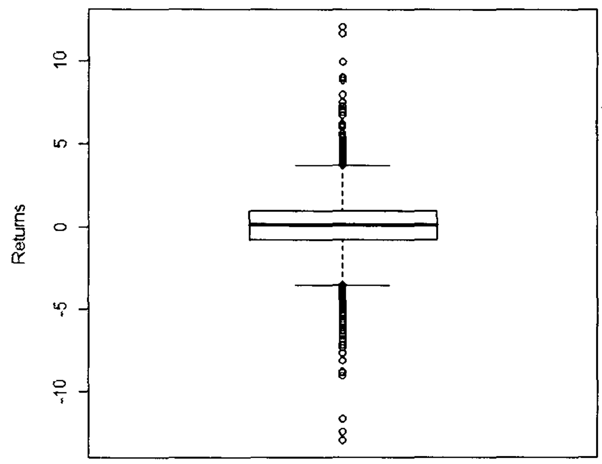
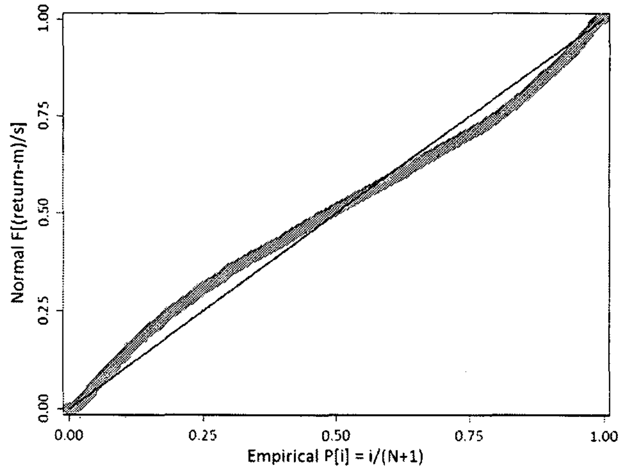


Figure 2.9: Normal Probability Plot of Daily Returns



the box are outliers or extreme observations. From Figure §2.8 we can see that, the return distribution has a thin mid–spread, though symmetric. But, it is characterised by long tails at either ends, as can be seen from the size of the outliers. An even more powerful method for examining the distribution is normal probability plots (Figure §2.9). It graphs the standardized random variable with the original random variable. If x is the random variable with mean μ and variance σ^2, then the standardised variable

$$z = \frac{x - \mu}{\sigma} \tag{2.4}$$

If x is Gaussian random variable, then a graph of its sample values with the values of z derived from the theoretical unit normal c.d.f should be a 45^0 straight line from the origin. When the tails of empirical frequency distributions are longer than expected of a normal distribution, the graph takes an elongated S form with the curvature at the top and bottom varying directly with the excess of relative frequency in the tails of empirical distribution (Fama, 1965). Such an observed shape is also accentuated by the fact that the center of the returns distribution are higher than the normal distribution, making the middle of empirical plot steeper than the one following strict normality.

We see that the empirical distribution of returns depart from normality. Fama (1965) argues that such departures from normality of the stock prices are in the direction predicted by Mandelbrot Hypothesis of a Stable Paretian distribution. Table §2.3 compares the empirical frequency distribution of returns from S&P CNX Nifty with that of unit normal and Fama's estimates. We can see that Nifty returns treads closer to Fama's estimates than that of unit normal.

A stable paretian distribution is characterized by four parameters – a location parameter δ, a scale parameter γ, an index of skewness β and a measure of the height of the tail areas of the distribution which Fama calls 'the characteristic exponent α'. If α is 1, then δ is the mean of the distribution. The parameter α can take any values between $0 < \alpha \leq 2$. When it is 2, the distribution is normal. Otherwise, the tails will be higher than the normal distribution. Larger the probability in the extreme tails, the smaller the value of α. Variance is finite or exists only in the case of α being two, and the mean exists when $\alpha \geq 1$. Wise (1963) has shown that as long as the characteristic exponent of α of the underlying stable Paretian process is greater than 1, the serial correlation coefficient defined as covariance of the returns upon its variance is a consistent and unbiased estimate of the true serial correlation of the population, as the sample size approaches infinity (Fama, 1965). Finding the value of the character exponent α is beyond the scope of this paper.

The implication of departure from normality or following a Stable Paretian distribution are many. First, the size of the total will be more than likely to be the result of a few very large changes that took place during much shorter sub–periods, unlike normal where individual price change is smaller compared to the total change. Second, the path of the price change is dis–continuous. Third, is the property of infinite variance. The implications of this last feature is that sample variance will show extremely erratic behaviour even for very large samples. Though sample variance is computable, population variance is infinite this makes measurements with sample variance meaningless (Fama, 1965).

Table 2.3: Comparison of Empirical Frequency Distribution with Unit Normal

σ from mean	Unit Normal	Fama's Estimates[a]	Nifty[b]
0.005	38.3	46.7	5.4
1	68.3	75.7	76.6
1.5	86.6	88.5	89.9
2	95.5	94.8	95.1
2.5	98.8	97.6	97.5
3	99.7	98.9	98.4
4	99.99	99.7	99.5
5	100	99.9	99.7
+5	0.00	0.1	0.3

[a] (Fama, 1965)
[b] Own Computation
[c] Data Source: NSE

2.3 Summary

By analysing the structural change in the series and the distributional properties of returns, it provides a platform for analysis for the rest of the thesis. Main conclusions which follow from this chapter is that; first, the market has gone through five phases (4 break points. Therefore, 4+1 regimes) which are not equally spaced. Therefore, any analysis should take account of these structural changes which the market has gone through. Second, the distribution of returns is better approximated by a stable Paretian distribution. Therefore, any analysis which requires the strict condition of normality has to be adopted with caution. But, more importantly it gives insight into the return generating process, which is that the aggregate change we observe is likely the result of large changes which occurred during short periods of time instead of an aggregation of incremental changes that occurred over a long horizon. This has major implication on the estimation method for testing the efficiency of the markets.

Chapter 3

Tests for Weak-Form Efficiency: A Non-parametric Approach

In Chapter§2 we saw that the market has gone through four periods of structural changes. We also saw that the distribution of returns is better approximated, not by Normal distribution, but by a stable paretian distribution. It is in this light that we undertake tests for weak form efficiency here. Using nonparametric techniques we test the weak-form efficiency of EMH that returns are unpredictable and random, such that excess returns cannot be generated through historical data analysis. Using runs test we first examine the randomness of return behaviour across structural breaks. Then we analyse the historical data of returns to see whether anomalies to EMH exists that makes predictability of returns possible.

The chapter is arranged as follows: Section§3.1 examines the theoretical foundations of weak-form efficiency. The technique and results of runs-test is provided in section§3.2. The issue of market anomalies is examined in section§3.3.

3.1 Testing Market Efficiency: Theory

Since Fama (1970) it is widely accepted that tests for market efficiency should be a test for Joint Hypothesis with an equilibrium asset pricing model. That is security markets are informationally efficient and returns follow a pre-specified equilibrium model (e.g. CAPM)

If the current prices fully reflect all available information then,

$$p_t^e = \varphi(\phi_t) \tag{3.1}$$

and

$$p_t^e = \varphi(\phi_t^m) \tag{3.2}$$

That is,

$$p_t^e = \varphi(\phi_t) = \varphi(\phi_t^m) \tag{3.3}$$

Where,

p_t^e = Equilibrium asset prices at time t

ϕ_t = Information set available to investors at time t

ϕ_t^m = Equilibrium prices actually used by the investors in the determination of asset prices at time t

$\varphi(.)$ is the model of equilibrium that links a particular information set with equilibrium prices

Equilibrium prices derived from the information set investors actually used are identical to the equilibrium prices implied by the set of all available information. If EMH is true in a world of certainty, no investor could earn supernormal profits by predicting prices from available information, since all relevant information will be reflected in asset prices. If EMH is true in a world of uncertainty, then no investor should expect to earn returns in excess of those normally associated with risky portfolios by predicting asset prices from the set of available information (Hess and Reinganum, 1979).

In this revised framework, market efficiency is tested with respect to an equilibrium asset pricing model. In which case it tests the joint hypothesis that security markets are informationally efficient and returns behave according to a pre–specified equilibrium model. But, this leads us to the joint hypothesis problem. That is, if the joint hypothesis is rejected we cannot attribute the rejection to either of it. Many economists (Schleifer, 2000) describe this as the ingenuity of Fama, because if joint hypothesis is the correct way of testing market efficiency then EMH can never be discarded!

Popular equilibrium models used for joint hypothesis testing are CAPM or the market model and their variants. It models cross–sectional returns as a function of market returns or risk and other firm–specific characteristics. But, the focus here is in modeling market returns itself, for which these models cannot be simply adopted as it is. Since a market index discounts economy wide information, a general equilibrium model might be a better predictor of its behaviour. This is, but, beyond the scope of this paper. More importantly the objective of this research is not to provide a 'verdict' on efficiency. Instead, it is broader in scope to analyse how the market has been behaving over time given our understanding about the features of market efficiency. May be, it can be more correctly described as an examination of relative efficiency, relative to time. If the concept of joint hypothesis has to be forced in, then we are testing the joint hypothesis that the market is efficient and the prices follow a random walk

The statement that, having the current price fully reflecting the available information, the successive (one–period) price changes are independent; and the successive price changes are identically distributed, together constitute the random walk hypothesis (See section §1.2 for the derivation of random walk model of asset prices [1]). Formally, the model says that

$$f(r_{t+1}|\phi_t) = f(r_{t+1}), \tag{3.4}$$

the conditional and marginal probability distributions of an independent random variable (see equation 1.8 also) are identical and the density function f must be the same for all t (Fama, 1970). In the random walk literature the information set is usually assumed to include only the historical data.

EMH specifies return behaviour as $E(r_{t+1}|\phi_t^m) = \mu$. When we say μ is constant over time, it does not imply that the value of μ is same throughout the history and life of the scrip or the market. It is, indeed, more realistic to consider μ to adjust to changes in the structural features in the

[1]It is more prudent to say, 'random walk with drift', since expected price change can be non–zero (Fama, 1970)

market or the economy. While the short-term fluctuations cancel-out each other, under the impact of a structural change it might move to a different level and remain there until the market undergoes another structural change. Therefore, one should be careful in defining the 'long-term' average returns of the market. It will be prudent to split the long-term series into different periods of structural changes and analyse them separately. In section 2.1, periods of strucutral changes in the market was identified. Here, we examine the weak-efficiency of the market across these periods of structural changes.

In section 2.2 we saw that the distribution of returns is not normal, instead it follows a Stable Paretian distribution. In the discussion which ensued, we showed that the property of infinite population for this class of distribution makes variance based measurements meaningless. This implies that we not is a position to continue to use parametric estimators, since we are not in a position to prove that the characteristic exponent α is greater than 1. Therefore, all our analysis will be based on distribution free or nonparametric statistical techniques.

We test weak form efficiency using two approaches. First, we test whether successive price changes are random using the nonparametric technique of runs test. Second, we examine the market anomaly of seasonality of returns, which makes predictability of the direction of returns easier. This we first examine through exploratory data analysis and then testing using Spearman's rank correlation coefficient. All the tests are performed across periods of structural changes. Market efficiency is a dynamic concept and therefore, it is bound to undergo changes over the period of time with the evolution of the market. Technology has brought significant changes to the market micro-structure, operational efficiency and the speed of information arrival, which will all significantly improve information efficiency. In this context, we suspect that the longer the historical time series data one use to test efficiency, there is a higher chance of rejecting it.

3.2 Runs-Test: A Non-parametric Test for Random Order

Non-parametric tests are also known as distribution free tests, since they do not make restrictive assumptions about the shape of the population distribution. Though this advantage is important, it also faces the limitation that they loose information while converting values to non-parametric ranks. Also, they are not as sharp as parametric tests. This is the trade-off a researcher has to make. Here, we test for random order of the return distribution using 'runs-test'.

"A run is a sequence of identical occurrences preceded and followed by different occurrences or by none at all"(Levin and Rubin, 1997). Suppose, a sample of the returns behave as follows:

$$-1.6, +1.3, +1.1, +1.5, -0.9, -1.2, -2.3, -1.9, +2.6, +3.1$$

If a positive change is denoted by P and a negative change by N, then the sequence will contain 4 runs:

$$\underbrace{N}_{1st}, \underbrace{P, P, P}_{2nd}, \underbrace{N, N, N, N}_{3rd}, \underbrace{P, P}_{4th}$$

Let us denote n_1 as the number of occurrences of P and n_2 that of N. Both occur 5 times in the series. And, we denote r as the number of runs, which is 4. A one-sample runs test is based on the idea that too few or too many runs show that the sequence was not drawn random.

The mean and standard error of the r-statistic is computed as follows:

$$\mu_r = \frac{2n_1n_2}{n_1 + n_2} + 1 \tag{3.5}$$

$$\sigma_r = \sqrt{\frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)}} \tag{3.6}$$

The sampling distribution of r can be closely approximated by the normal distribution, in a one-sample runs-test, if n_1 or n_2 is larger than 20. We test the null hypothesis of random order against the alternative hypothesis of no random order, using the test statistic

$$z = \frac{r - \mu_r}{\sigma_r}$$

Results: Instead of positive and negative changes (i.e., zero as the cut-off) we take median as the cut-off value. That is, cases are defined as values above and below the median. The test of random order of returns in conducted seperately for returns falling within each structural breaks which corresponds to December 1994, July 1999, June 2003 and January 2006. The results of the runs-test are given in figure 3.1.

In the figure 3.1 variable p corresponds to log closing prices for the period 1991 to 2008 and the variable r denote the returns during this entire period. $r0$ corresponds the sample returns before the first break; $r1$ falls within the first and second break and so on. The last row in the table provides the significance or the p-value of the test statistic. We can see that except for variables r3 and r4, p-values are significant for all the other variables.

Analysing the structural breaks of the series gives interesting results. Runs-test rejects the null hypothesis of random order for the entire return series for the period 1991 to 2008. Which is rejection of weak-form efficiency. But, different sub-periods have behaved differently. While, the returns for the first three regimes do not comply with random order or independence, regimes 4 and 5 fit the EMH view of randomly distributed returns. This implies that lately market is moving towards the EMH view of weak-form efficiency. The results also support our earlier argument of results being sensitive to the period of analysis.

Figure 3.1: Runs-Test: Results

Runs Test

	p	r	r0	r1	r2	r3	r4
Test Value(a)	7.047908	.090039	.123141	-.048406	.042860	.2518369	.126955
Cases < Test Value	2139	2140	413	559	498	327	342
Cases >= Test Value	2142	2141	413	560	499	327	343
Total Cases	4281	4281	826	1119	997	654	685
Number of Runs	54	1887	331	480	443	321	330
Z	-63.817	-7.780	-5.779	-4.815	-3.581	-.548	-1.032
Asymp. Sig. (2-tailed)	.000	.000	.000	.000	.000	.584	.302

a Median

.3 Tests for Market Anomalies: The Case of Seasonality

> "October. This is one of the peculiarly dangerous months to speculate in stocks in. The others are July, January, September, April, November, May, March, June, December, August and February" [2]

For a phenomena to be an anomaly there has to be 'conventional wisdom' that the phenomenon violates [3]. The conventional wisdom about efficient markets is that there are little excess returns, relative to the market returns (and the level of risk) that one can make by analysing historical data. But, researchers have gathered systematic evidence about markets violating this conventional wisdom. Some of these are calender effects, small-firm or size effect etc. Here we examine a calender effect known as 'the-month-of-the-year-effect' and examine whether this 'much-hyped' anomaly is a persisting feature in the Indian market. While the presence of this anomaly would be a rejection of efficiency, its absence need not imply an acceptance of efficiency.

[2] Mark Twain (1894) in *The Tragedy of Pudd'nhead Wilson*, ch 13

[3] Bailey (2005, p. 72)

3.3.1 Review on Market Anomalies

Researchers bent over discovering anomalies in the stock market, to earn a quick buck, will discover unusual patterns emerging out of the most unusual of occurances. For example *investopedia* [4] circulated among its subscribers a list out what they called the 'world's wackiest indicators'. Most of it had no logic contained in them, but continue to have an embarrassing level of believers. For example, multiplying the change in the butter production in Bangladesh by two will give the percentage by which S&P 500 Index will change the next year. Or "When the majority of a country dislikes the man in the White House, the stock market is supposed to soar."

Leaving these embarrassments part, there has been scientific economic evidence countering market efficiency. One of the earliest relates to the Capital Asset Pricing Model (CAPM) specification. It was shown that value based measure have higher explanatory power than the beta[5]. Basu's (1977) this result was later confirmed by Reinganum (1981). They found US stock returns to be positively related with price to earnings ratios. Later, others documented similar relation with Book–to–price ratio and dividend yields[6]. Later Banz (1981) showed that in the US stock markets there is a negative relation between security returns and the market value of the firm. This anomaly is popularly known as the size effect. All these evidences led to the understanding towards a better multi–factor asset pricing models such as the popular Fama–French three–factor model (Fama and French, 1992)[7]. Coming back to anomalies, Shiller (1981) showed that prices wander away from fundamental values since the variation in

[4] http://www.investopedia.com/articles/stocks/08/stock-market-indicators.asp?viewed=1

[5] CAPM can be specified as:

$$r_j = a_0 + a_1\beta_j + \sum a_j C_{ij} + e_j \tag{3.7}$$

Where,r_j = Cross sectional returns of security j; β_j = Covariance with the market return; C_{ij} = Security specific characteristics. CAPM predicts that the a_j is zero $\forall j > 1$

[6] The relation with dividen–yield could be due to the differential taxation of capital gains and ordinary income. See Litzenberg and Ramaswamy (1979)

[7] Fama and French suggest that the additional variables proxy risk factors omitted from CAPM

stock prices are too large to be explained by variation in dividend payments[8]. Coming to long–horizon returns, DeBondt and Thaler (1985) finds that stocks which underperformed over a period of 3 to 5 years average the highest market–adjusted return over the subsequent period. This long-term mis-pricing is seen as an overreaction in the market in which stocks diverge from fundamental value.

Literature is also abound on stock market seasonalites. Documented seasonalities include month-of-the-year, week-of-the-month, day-of-the-week and hour-of-the-day effects. Rozeff and Kinney (1976) first documented that average stock returns in January are higher than any other month. Keim (1983) and others[9] also finds the same, that the fifty percent of the annual price premium in the US is concentrated in the month of January, particularly in the first few weeks of the year. This is particularly true for small firm stocks. One explanation attributed to this behavior is the year end related tax selling and the subsequent repurchases in January. By selling stocks that have reduced in prices, particularly smallcap stocks, traders realize a capital loss which can be used to offset capital gains, thus reducing the taxable income. This is popularly known as the tax loss selling hypothesis. Another explanation relates to the portfolio rebalancing by institutional investors. The fund mangers sell small stocks showing losses in the current year and reinvest the funds in selected stocks in early January. The motivation for this is that, it will make their annual reports look stronger leading to higher compensation for the manager [10]. Ogden (1990) gives a varied explanation for the monthly and January effects. He attribute it, in part, due to the standardization in the payments system (in US). The cash flows is concentrated at the turn of each calendar month. Due to this standardization, investors realize substantial cash receipts at the turn of the month and year. Which, when reinvested leads to a surge in stock returns at the turn of the month. He calls it, the 'Turn of the month

[8]"Measures of stock price volatility over the past century appear to be far too high – five to thirteen times too high – to be attributed to new information about future real dividends" (Shiller, 1981)

[9]Roll (1983), Reinganum (1983), Ritter (1988)

[10]See Ogden (1990)

liquidity hypothesis', since it depends on the magnitude of aggregate liquid profits realized in the month, which is affected by monetary policy. Since turn of each month is a typical pay off date, short–term investable funds prefer securities maturing at the end of the calender month to securities maturing either before or after that date [11]. This demand for month end securities causes their prices (yields) to be bid up (down) relative to adjacent maturity securities. In explaining January Effect he says that, his hypothesis is consistent with observed concentration of positive returns in the first few trading days of January. Besides, there is a surge in retail activity in the end of year (holiday effect) and the consequent liquid profits in December is expected to induce a large surge in stock returns in early January.

A recent paper by Pandey (2002) which examined the Bombay Stock Exchange's benchmark index 'Sensex' for the period 1991 to 2002 confirm the existence of seasonality and the January effect in the Indian market. He examines seasonality using an augmented dummy variable regression, taking January as the omitted category or benchmark category in the model and replacing the residuals with an ARIMA model.

Bailey(2005) points out that the feature of financial anomalies is that they tend to disappear soon after evidence of their existence enters the public domain. This is because either they signal profitable investment opportunities which disappear when they become widely know, or because they were never genuine (Bailey, 2005). Here we examine whether any anomaly exists in the form of seasonality in monthly returns.

[11] If it is in shorter term securities, it may have to be rolled over to provide the necessary liquidity to pay turn of the month obligations. Or if it is in longer term securities it will have to be sold prematurely. Either ways it is suboptimal due to the high interest rate risk and transaction cost invloved.

3.3.2 Seasonality in Nifty: Month-of-the-Year Effect

Exploratory Data Analysis:

A bar-graph of the mean across the months provides an easy visual explanation on the prevalence of seasonality. Figure 3.2 is such a bar chart on mean daily returns on Nifty for the period January 1991 to Ocotber 2008 for various months. From the bar-graph we can see that the calender months of February and December has the highest mean daily returns, over and above 0.2%. The month of October register the lowest mean daily return of about -0.14%. The calender months of March, April and May are the only other months reporting negative mean daily returns.

Table 3.1 gives the mean daily returns for each month in each year. From this we compute, the probability of having negative mean daily returns in each month (see table 3.2). We define the probability of having negative returns simply as the ratio of the frequency of a given month having mean negative returns for the period 1991 to 2008 to the total frequency possible. From this we can see that the calender months of March and April has the highest probability (72% and 67%, respectively), while the December and November has the lowest (22% and 28%, respectively). But, one should be careful at 'theorizing' at the mere sight of such patterns. For example on can attribute the low returns in October as emerging out of advance tax-filing or consumers adjusting their cash flows for the upcoming holiday season. Similarly, March will coincide with the financial year end. One can put forward the tax-loss selling hypothesis, borrowing the idea from the US markets (In the US, financial year coincides with the calender year. The observed low returns during December and high returns during January is attributed to tax-loss selling to reduce the tax-burden in December, which is followed by a buy-back in January). But, unlike in US we don't see buy back the following month leading to an 'April effect'. But, it might be possible that they are just 'random' occurrence, and might not contain any persisting patterns to it.

It would be more insightful to examine the monthly performance across structural breaks. Such an analysis will provide a disaggregated look at the

Table 3.1: Average Daily Returns: Across Months, Across Years

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
1991	-0.16	1.05	-0.23	0.30	0.21	-0.15	1.15	0.34	0.27	0.01	0.10	-0.05	0.24
1992	0.97	1.45	2.19	-1.10	-1.94	0.35	-0.90	0.54	0.49	-0.98	-0.64	0.31	0.06
1993	0.19	-0.07	-0.79	-0.35	0.29	0.08	0.29	0.77	0.16	-0.07	1.12	0.53	0.18
1994	0.94	0.40	-0.65	-0.13	0.16	0.24	0.11	0.40	-0.31	-0.09	-0.11	-0.31	0.05
1995	-0.47	-0.29	-0.13	-0.31	0.27	-0.17	0.17	-0.13	0.19	-0.13	-0.62	0.26	-0.11
1996	-0.31	0.78	-0.04	0.59	-0.10	0.15	-0.33	-0.06	-0.41	-0.18	-0.43	0.42	0.01
1997	0.36	0.13	-0.16	0.57	-0.13	0.60	0.11	-0.50	0.08	-0.21	-0.31	0.24	0.07
1998	-0.54	0.51	0.25	0.19	-0.46	-0.55	-0.05	-0.44	0.27	-0.47	-0.04	0.36	-0.08
1999	0.47	0.07	0.43	-0.49	0.70	0.22	0.45	0.34	0.00	-0.30	0.18	0.33	0.20
2000	0.22	0.32	-0.38	-0.46	-0.09	0.29	-0.47	0.20	-0.46	-0.39	0.36	-0.02	-0.07
2001	0.37	-0.07	-0.78	-0.11	0.17	-0.25	-0.15	-0.09	-0.71	0.29	0.47	-0.04	-0.07
2002	0.07	0.30	-0.06	-0.19	-0.24	0.14	-0.43	0.25	-0.24	-0.06	0.52	0.19	0.02
2003	-0.21	0.11	-0.42	-0.23	0.36	0.57	0.19	0.67	0.20	0.41	0.19	0.69	0.21
2004	-0.18	-0.03	-0.07	0.07	-0.91	0.07	0.37	0.00	0.31	0.12	0.46	0.26	0.04
2005	-0.06	0.11	-0.15	-0.34	0.42	0.27	0.20	0.14	0.41	-0.46	0.56	0.31	0.12
2006	0.28	0.13	0.46	0.25	-0.67	0.08	0.02	0.38	0.24	0.21	0.25	0.02	0.14
2007	0.14	-0.45	0.10	0.34	0.24	0.02	0.22	-0.07	0.59	0.73	-0.11	0.33	0.17
2008	-0.77	0.08	-0.55	0.44	-0.29	-0.89	0.30	0.03	-0.51	-1.91			-0.41
Average	0.07	0.25	-0.05	-0.05	-0.11	0.06	0.07	0.15	0.03	-0.19	0.11	0.23	0.05

Figure 3.2: Seasonality in Nifty: Month of the Year Effect

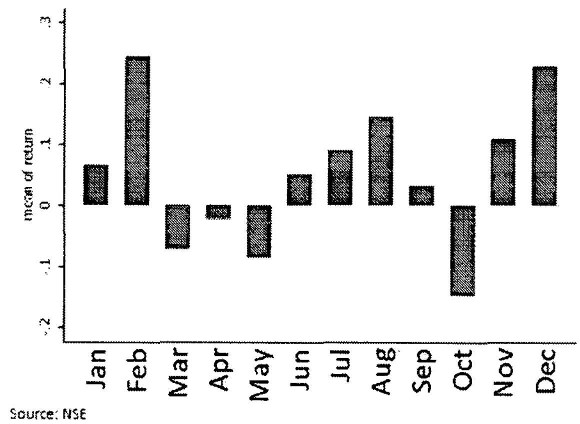


Table 3.2: Percentage of Times a Month Gave Negative Returns[a]

Month	Jan	Feb	Mar	Apr	May	Jun
%	44%	28%	72%	56%	50%	28%
Month	Jul	Aug	Sep	Oct	Nov	Dec
%	33%	33%	33%	67%	39%	22%

[a] Own computation

Table 3.3: Monthly Mean Daily Returns Across Periods[a]

Month	Regime1	Regime2	Regime3	Regime4	Regime5
Jan	0.61	-0.11	0.11	-0.04	-0.25
Feb	0.68	0.24	0.17	0.04	-0.08
Mar	0.02	0.08	-0.42	-0.11	0.04
Apr	-0.23	0.13	-0.24	-0.14	0.34
May	-0.24	0.06	0.05	-0.23	-0.25
Jun	0.11	0.04	0.16	0.21	-0.25
Jul	0.29	-0.02	-0.16	0.26	0.19
Aug	0.50	-0.29	0.18	0.26	0.12
Sep	0.14	0.04	-0.35	0.30	0.10
Oct	-0.25	-0.25	-0.11	0.04	-0.15
Nov	0.12	-0.35	0.38	0.40	0.07
Dec	0.11	0.27	0.12	0.42	0.17

[a] Own computation. Source data from NSE

time series, but at the same time provides enough aggregation which an year-to-year analysis cannot provide. Besides, while markets behave differently across different regimes, there might be fair amount of consistency in behaviour within the regimes. The observations from the bar graphs can be summarised as follows:

Regime1-Jan'91 to Dec'94: The mean daily returns are highest for February and January (above 0.6%), followed by August (0.45%). April, May and October gave negative returns less than -0.2% (Fig3.3).

Regime2-Dec'94 to Jul'99: Average daily returns are more than 0.2% during the months of December and February. It is lowest for November. August, October and January also have negative returns (Fig.3.4).

Figure 3.3: Mean Returns for Regime1

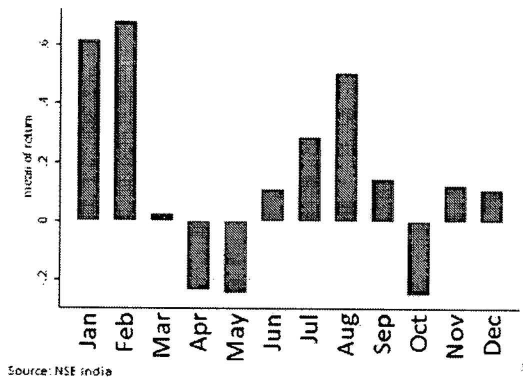


Figure 3.4: Mean Returns for Regime2

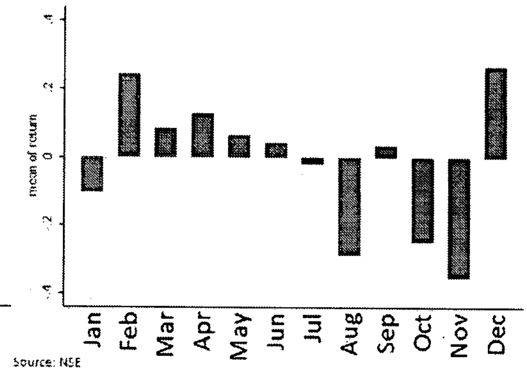


Figure 3.5: Mean Returns for Regime3

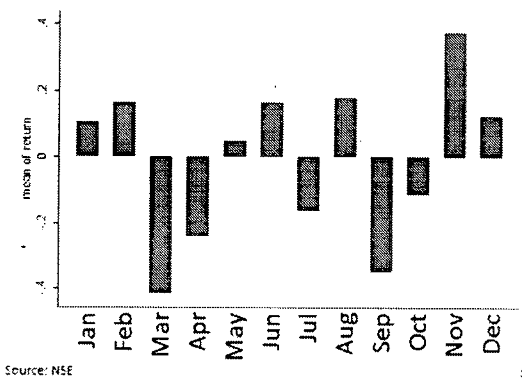


Figure 3.6: Mean Returns for Regime4

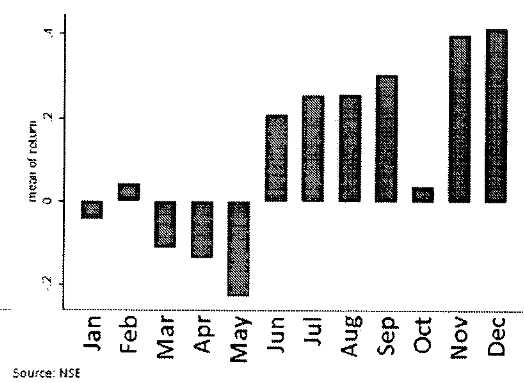
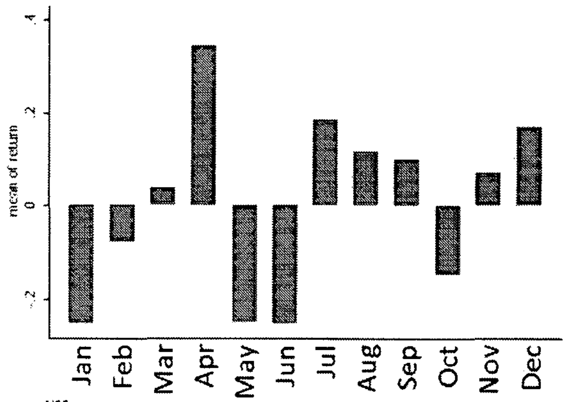


Figure 3.7: Mean Returns for Regime5



Source: NSE

Regime3-Jul'99 to Jun'03: Highest positive returns for November and lowest returns for March, followed by September. (Fig.3.5)

Regime4-Jun'03 to Jan'06: December and November have the highest daily returns (above 0.4%). May has the lowest returns. April, March and January also have negative returns (Fig.3.6).

Regime5-Jan'06 to Oct'08: April registered the highest return and January, May and June has the lowest (Fig.3.7).

Tables 3.4 and 3.5 summarizes the top performers and worst performers across these regimes. On looking at these two tables we are able to appreciate the wisdom contained in Mark Twain's words which was quoted in the opening of this chapter. We can see 7 out of 12 months appearing at different points of time as the worst performers! We neither see consistent January effect nor a tax-loss selling effect.

Nonparametric test for seasonality:

Here we devise a statistical test for seasonality based on nonparametric techniques. If seasonality or month-of-the-year persists, by ranking the

Table 3.4: Month of the Year Effect: The top Performers [a]

Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
February	December	November	December	April
January	February	September	November	July

[a] Own computation. Source data from NSE

Table 3.5: Month of the Year Effect: The Worst Performers [a]

Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
October	November	March	May	Jan
May	August	September	April	May
April	October	April	March	June

[a] Own computation. Source data from NSE

months according to the size of their mean daily returns we might see similarity in these ranks across years. But, instead of yearly ranks it would be better to examine it across periods of structural breaks, as it can provide a fair amount aggregation and at the same time provide the essence of persisting patterns. We, therefore, rank months according to their mean daily returns across the five regimes. Then, we test whether these ranks are consistent across the periods by examining rank correlation coefficient between different periods.

Table 3.6 provides the ranking of months based on the mean daily returns, across the periods of structural breaks. January had ranks ranging from 2 to 11. Rank of February has ranged from 1 to 8, starting with rank 1 and then slowly departing from the top position to 2, 3, 7 and then 8 in the final regime. March also had sufficient variability ranging from 4 to 12. April had a nearly alternating pattern with highest and lowest ranks ranging from 11 in regime-four to 1 in regime-five. May and June's ranks range from 5 to 12 and 4 to 12 respectively. We can also see that less

Table 3.6: Ranking of Months Based on Mean Daily Returns Across Periods [a]

Month	Regime1	Regime2	Regime3	Regime4	Regime5
Jan	2	9	6	9	11
Feb	1	2	3	7	8
Mar	9	4	12	10	7
Apr	10	3	10	11	1
May	11	5	7	12	10
Jun	8	6	4	6	12
Jul	4	8	9	5	2
Aug	3	11	2	4	4
Sep	5	7	11	3	5
Oct	12	10	8	8	9
Nov	6	12	1	2	6
Dec	7	1	5	1	3

[a] Own computation using closing price data from NSE

'controversial' months such as April and July topping the list in the latest regime. August, which was ranked 11 in second regime, is now ranked 4. November had huge variability moving from 12 in the second regime to rank 1 in the third regime. In the latest regime we can find it at 6. October had a low variability at lower ranks - 9 to 12; and December had the low variability at higher ranks - 1 to 7. In short, we do not see any consistent pattern across these months, and they move around with great variability.

To test for consistency in the rankings we use Spearman's rank correlation coefficient. The computations involved in getting the coefficient between two rankings are as follows: First rank the two series. Obtain D, which is the difference between two. Then the rank order correlation can be computed by the equation:

$$\rho = 1 - \frac{6 \sum D^2}{N(N^2 - 1)} \tag{3.8}$$

where, N equals the number of pairs and ρ is the rank correlation coefficient. This exercise can be conducted for all pairs of rankings and the results can be presented in a correlation matrix (see table 3.7). These results can be supplemented using Kendall's coefficient of concordance, which can simultaneously measure the degree of relationship with all the sets of ranks. For this we first compute $D*$, is the difference of the sum of the ranks of reach row from this mean. We take sum of ranks and divide it by the number of months to get the average sum of ranks. $D*$ Next we can use the following formula to compute the Kendall's coefficient of concordance, W:

$$W = \frac{12 \sum D*^2}{m^2(N)(N^2 - 1)} \tag{3.9}$$

Where, m is the number of rankings, which is five in our case; N is the number of cases ranked, which is 12 and W is the Kendall's coefficient of concordance. A perfect agreement is indicated by a W=1 and a lack of agreement by a W=0 (Downie and Heath, 1970).

The results from rank correlation coefficients also confirm our observations from exploratory data analysis that there are no persisting patterns

Table 3.7: Rank Correlation Coefficients: Monthly Ranking Across Periods [a]

	Statistic	Regime1	Regime2	Regime3	Regime4	Regime5
Regime1	Rho	1				
Regime2	Rho	-0.13	1			
	sig. level	-0.68				
Regime3	Rho	0.41	-0.29	1		
	sig. level	-0.18	-0.35			
Regime4	Rho	0.41	-0.23	0.44	1	
	sig. level	-0.17	-0.47	-0.15		
Regime5	Rho	0.08	0.14	-0.21	0.34	1
	sig. level	0.79	0.64	0.49	0.27	

[a] Own computation

in monthly returns. On examining the results of Spearman's rank correlation coefficients matrix in table 3.7, we find neither high correlation coefficients nor statistical significance. This result indicate a rejection of the presence of seasonality persisting in the Indian markets. Our computation of Kendall's W

$$W = \frac{12(1500)}{(25)(12)(144-1)} = 0.42 \tag{3.10}$$

also indicates that concordance between the rankings is low.

Recap :

This section examined whether anomalies to market efficiency in the form of seasonality in returns exists. The results of our exploratory data analysis and nonparametric tests rejects the presence of seasonality persisting in the Indian market. Sullivan *et al* points out that "In the limited sample sizes typically encountered in economic studies, systematic patterns and apparently significant relations are bound to occur if the data are analyzed with sufficient intensity" (Sullivan, Timmermann, and White, 1998). While pointing out at the dangers of data driven inference in analysing calender effects, they also cautions about data snooping bias[12]. He reminds us that none of these calender effects were preceded by a theoretical model predicting their existence. It is not sure whether we have over–indulged in data analysis, but we do suffer from data–snooping bias. At this point, it will be preferable to stop short of theorizing further on the possibilities of a 'month-of-the-year' effect.

3.4 Summary

This chapter examined the issue of weak form efficiency. Presence of structural breaks in the price series and the evidence of the returns following a paretian distribution made us to perform tests based on nonparametric methods across the periods of structural breaks. To test our hypothesis that successive price changes are independent, we employed runs-test. The runs-test result rejected the hypothesis of price changes being randomly ordered. One can argue that the runs-tests' rejection of the random ordering of the returns series is a direct rejection of the Bacelior-Osborne hypothesis of the stock market behaviour; and that, there is more to the market than the theoretically bounded realms of rationality. In this context it is important to understand and better appreciate the market from a behavioural perspective. As Shiller had pointed out, as long as human beings form the market, their instincts will be built into it and therefore the market will be always and everywhere inefficient. But, one need not take such an extreme stand either. Efficient markets provides us with a comfortable litmus test to see the sophistication of the market – is there enough play-

[12]"Like many of the social sciences, economics predominantly studies non-experimental data and thus does not have the advantage of being able to test hypotheses independently of the data that gave rise to them in the first instance. If not accounted for, this practice, referred to as data-snooping, can generate serious biases in statistical inference"(Sullivan, Timmermann, and White, 1998)

ers in the market who has exploited all the available information such that, outside noise, only new information can 'move' the market. With regard to weak-from efficiency and serial correlation is concerned, it is not the simple presence of serial correlation that is of interest - but, the ability to exploit this information in a trading strategy.

But, a closer examination across the periods of structural breaks showed that weak-form inefficiency is not the case since the fourth regime beginning in July 1999. That is, lately market has begun to tend towards the theoretical ideal of weak form efficiency as evidenced by the returns being independently distributed. This could be on account of improvements in operational efficiency achieved due to better application of information and communication technology in trading. Identifying factors responsible for improving efficiency is a research in itself. In this context, the results opens up further areas of research for identifying causes for efficiency that can range from market integration to foreign institutional investors to rise in market participation, about which we do not wish to speculate here.

The chapter also examined the issue of predictability of returns under the presence of seasonality. The exploratory data analysis and nonparametric test of rank correlation coefficients do not detect any seasonality for India. We are of the opinion that any such analysis of seasonality should take into consideration the dangers of excessive data analysis and data snooping bias.

Our results are important in the context of existing literature on weak form efficiency. Firstly, the periodisation based analysis was able to show the dynamics of weak form efficiency over time. The market has moved from inefficiency to efficiency. Secondly, all our analysis are based on nonparametric methods in the light of our evidence that the return distribution is stable paretian. Thirdly, we contradict the earlier evidence of the presence of seasonality, our results being based on nonparametric techniques.

Chapter 4

Semi-strong form efficiency: The case of monetary policy announcements

Monetary policy is a major liver through which the short-term macro fine-tuning is made possible. By adjusting the liquidity and cost of funds in the economy, it exerts considerable influence over the investment decisions and other economic activities. It influences stock market in two ways. First, it directly effects trading in securities by affecting liquidity available for speculative activities. Second, it influence the expectations in the market by throwing out signals in the form of an expansionary or contractionary policy.

This chapter presents what we call a 'precursor to event study'. It is an event study because we are analysing the outcome of a particular event on the stock market behaviour. But, it is not entirely an event study because of the difference in the methodology we employ and the objective; and therefore, we call it a precursor. The objective is not one of examining market efficiency. Instead, it is descriptive in nature, trying to explore whether there is any relation between the information content in the monetary policy and the resulting stock market behavior, *prima facie*. But, there is a significant methodological difference from other studies since our analysis are based on nonparametric statistics. The evidence in this regard is expected to point out into the scope and need for further research in this direction.

Section§4.1.1 discusses the literature linking monetary policy and equity markets. Section§4.1.2 gives a brief discussion on event studies literature. Section§4.2 introduces the data and methodology used. The results from exploratory data analysis is provided in section§4.3, nonon-parametric statistical testing is introduced in section§4.4. Concluding observations from this exercise is provided in section§4.5.

4.1 Literature Review

4.1.1 Monetary Policy and Equity Markets

As mentioned above, monetary policy can affect the present value of the future flow of earnings and hence influence equity prices. But there are many ways in which monetary policy can affect the future flow of earnings. It can be in the form of credit market channel of monetary transmission mechanism (MTM), interest channel of MTM or even stock market channel — the latter, probably being an area which is relatively under–explored. The direct impact of a monetary policy stance on the equity markets is sometimes difficult to analyse, because at times the policy itself could be a reaction to the market and become endogenous.

With regard to MTM channels Bernanke (2003) shows that the effect of monetary policy on the markets through real interest rate is very little. Instead, the reaction is driven by affecting the expected future excess returns and to some extent by expected future dividends. When it comes to the credit market channel, a contractionary policy affects those firms who are highly bank dependent borrowers, as banks reduce their overall supply of credit (Kashyap, 1993). This is on two accounts: First, with rising interest rates the present value of collaterals will fall adversely affecting their balance sheets. Second, though information asymmetries prevail in the market, at times, divulging information pays. For instance, during the times of credit squeeze banks tend to limit their credit lines. In such periods, firms with less publicly available information may find it difficult to access bank loans (Gertler, 1994).

So, the ingredient here is the firm–specific attributes. That is, monetary policy affect each firm differently depending on their firm specific and industry specific characteristics, and therefore the equity prices will react accordingly. Thorbecke (1997) shows that response of stock returns to monetary policy is larger for small firms. Ehrmann and Fratzscher (2004) shows that the effect on financially constrained firms is much larger — the impact of monetary policy on firms with low cash flows and low debt to capital ratio is twice as much as those with high cash flow and debt. Similarly, sectors which are cyclical and capital intensive react two to three times more than non-cyclical industries.

It has been well–documented that monetary policy affects returns through "shocks". Ehrmann and Fratzscher (2004) analysing the S&P500 of the US markets, finds that an unexpected tightening of 50 basis points decreases return by 3% on the day of the announcement. With respect to monetary policy shocks, the market reacts strongly when the changes are unexpected, when there is a directional change to the policy or during periods of high volatality in the market.

4.1.2 Event Studies

The semi–strong form efficiency states that investors cannot make excess returns using any publicly available information. Since, the moment the information becomes public it gets immediately incorporated in the prices. This makes an investor unable to gain by using this information to predict the returns. After Fama (1991) such studies are increasingly called as event studies. The later gives an excellent review of literature on event study relating to firm level announcements and events in the US markets, but leaves review of macroeconomic events to others.

The usual purpose for which an event study is employed in financial economics literature is to measure the effect of an event of interest on the value of the firm. Given the neoclassical assumptions about the market, one expects the market prices to react correctly and immediately to the event.

One of the first studies in this regard was by Dolley (1933), who examined the price effects of stock splits. But, the methodology of event study as we see today saw its beginnings, more or less, in Fama, Fisher, Jensen, and Roll (1969). They also focus on the effect of stock splits, with the additional dimension of having removed the effects of simultaneous dividend increases.

Some of the major event studies relating monetary policy and equity markets are by Thorbecke (1997),Lobo (2000), Kuttner (2001), Bomfim (2003), Kuttner (2001) etc.

Thorbecke (1997) examines the reaction of the markets on days when changes to Federal fund rates are announced for the period 1987 to 94. He finds the US equity index reacts significantly to policy announcements. Lobo (2000) showed that in the US market for the period 1990-1998, the impact of a monetary tightening was much stronger than monetary easing. Bomfim (2003) finds that volatility is lower on days before the monetary policy announcement and increases substantially after the decision is made. Kuttner (2001) saw that during a policy announcement markets are reacting to the unexpected component in the policy, which has yet not been discounted. Ehrmann and Fratzscher (2004), which was discussed earlier, also analysed the market by separating out the surprise component. He measures surprise as the difference between the announcement of the FOMC decision and the market expectation. The data from Reuters Poll conducted among market participants on Fridays before each FOMC meeting was used here to arrive at the market expectation.

Agrawal (2007) recently examined the impact of announcements by the Reserve Bank of India on the Indian market. He examines 6 announcements affecting CRR between April 2006 and July 2007, classified as 'good news' and 'bad news'. A hike in CRR is considered as a bad news, and a good news is when, contrary to popular belief to control inflation, RBI leaves CRR unchanged. The study takes an event window of 31 days — 15 days before the event and 15 days after it. The data used is the cross-sectional daily returns of the 50 stocks constituting Nifty. Abnormal returns is taken as the residual of the Sharpe-Linter market model of modelling cross-sectional returns as a function of the market return (daily returns of the index. Here, CNX Nifty). The variable of interest is the cumulative average abnormal returns. Where, average abnormal returns is the average of the abnormal returns during the event (30 days). By adding this he arrives at cumulative average abnormal returns. He shows that CAARs does not normalize after the event, indicating that market is slow in incorporating the content of the monetary policy announcements. This, he argues, is evidence for weak form inefficiency. Though a very interesting study, one can point out some caveats. The impact of monetary policy on different sectors will be different. That is, it would add to the analysis if one could group the firms based on some criteria for such a disaggregated analysis. But, to see the impact of the policy on the market, examining the index is better since it evens out different firm level information reaching the market and reflects only those which affects all the firms together. With regard to the event window, such a large window assumes that policy announcement is the only additional information that has happened during the event. The study defines 'good news' as a policy announcement which was in contradiction to the market-wide expectations. That is, though the market expects the policy to be contractionary to curb inflation, it was actually left unchanged. Therefore, the study is actually looking at the unexpected component with respect to good news. The result that the market reacts positively before the announcement, therefore, would imply that markets are efficient in the sense that the information was anticipated correctly.

We depart from other studies methodologically, as we continue to use nonparametric techniques in this event study and examines all the monetary policy announcements in India after the introduction of Nifty in November 1995.

Table 4.1: Frequency of Monetary Policy Announcement by Periods

	Regime2	Regime3	Regime4	Regime5	Total
Expansionary	15	15	1	0	31
Contractionary	5	1	5	15	26
Total	20	16	6	15	57

[a] Data Source: RBI Annual Reports (various issues)

4.2 Data and Methodology

4.2.1 Data

We examine the trading days for the period from 1996 January to 2008 April, when there has been a change in the monetary policy stance. We primarily focus at the three major tools in the hands of RBI namely, Cash Reserve Ratio, Bank Rate, and Reverse repo rate; through which it affects the liquidity in the system (through CRR) and signals the interest rate in the economy (through Bank Rate) and adjusts short term liquidity (reverse repo rate). The policy announcement dates were compiled from the Annual Reports of Reserve Bank of India from 1996–97 to 2007-2008. This corresponds to the period Regime 2 to Regime 5. All together we analyse 57 policy announcements occurring during this period. The frequency of announcements across the periods is provided in table 4.1. There are 20 events during Regime2, 16 during Regime3, 6 in Regime4 and 15 in the last regime.

4.2.2 Methodology

We classify the policy date as expansionary or contractionary. The classification is made as follows: If

$$y_0^i - y_{-1}^i > 0; Contractionary \tag{4.1}$$

$$y_0^i - y_{-1}^i < 0; Expansionary \tag{4.2}$$

Where, y_0^i is the current policy stance and y_{-1}^i is the policy stance in the previous period. y is the policy variable and the superscript i differentiates policy instrument. From table 4.1 we can see that during the Regimes 2 and 3, the direction of the policy was mostly expansionary, and in the last two regimes contractionary policy dominated.

If the date of policy announcement is t, we examine the market behavior for the just preceding and succeeding the policy announcement. That is, our event window is $t-1$ to $t+1$, where t is the date of policy announcement.

We examine the impact of monetary policy announcements on the stock market during the event window to examine semi-strong efficiency of the Indian stock market. We first examine the impact of policy announcements during the event window using exploratory data analysis, and the results are later tested using nonparametric tests and this analysis carried across periods of structural breaks which are weak-form efficient since weak-form efficiency is a precondition for semi-strong efficiency.

4.3 Exploratory Data Analysis

A. Good News Vs. Bad News-I

Here we examine whether there is differences in the market behaviour between an expansionary policy announcement and a contractionary policy announcement. An expansionary policy announcement is good news for the market as it reduces the cost of funds and/or increases the liquidity available for investment as well as trading. As mentioned before, the event window is three days – constituting the day before announcement $(t-1)$, the day of announcement(t) and the day after announcement $(t+1)$, respectively.

From figure 4.1 we can see that within the event window, market gives a negative return during a contractionary policy announcement and

Figure 4.1: Mean Daily Returns Across Events

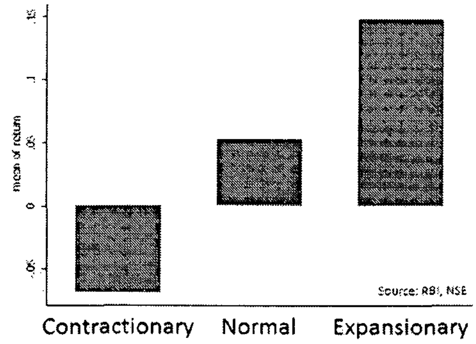


Table 4.2: Mean Daily Returns During the Event of Monetary Policy

Day	Contractionary	Expansionary
$t-1$	-0.29	0.39
t	-0.12	-0.05
$t+1$	0.18	0.07
Non-event days	0.05	0.05

[a] Data Source: RBI, NSE

a high positive return, compared to a normal trading day, during an expansionary policy announcement.

B. Good News Vs. Bad News-II

Here we undertake a more disaggregated examination of the impact of the announcement. We examine how the market behaves between each of the three days of our event window – that is, on the day of announcement (t) and on the days preceding $(t-1)$ and succeeding it $(t+1)$.

The day preceding an expansionary policy announcement gives the highest positive returns (0.39%). On the day an expansionary policy announcement we find negative returns of -0.05%, which reverts to a positive 0.07% the next day. Probably this is an indication of overreaction during

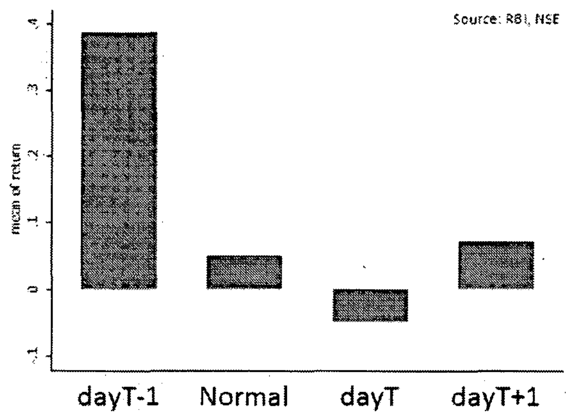


Figure 4.2: Expansionary Policy Event

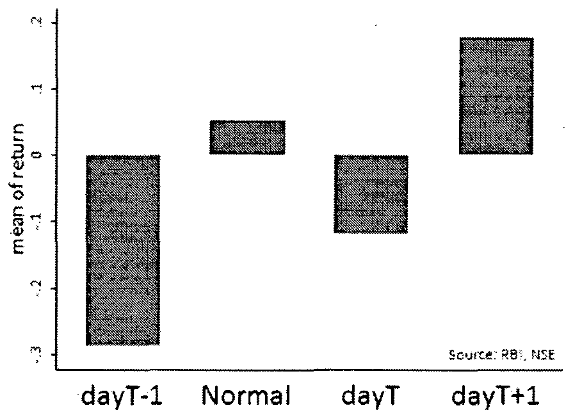
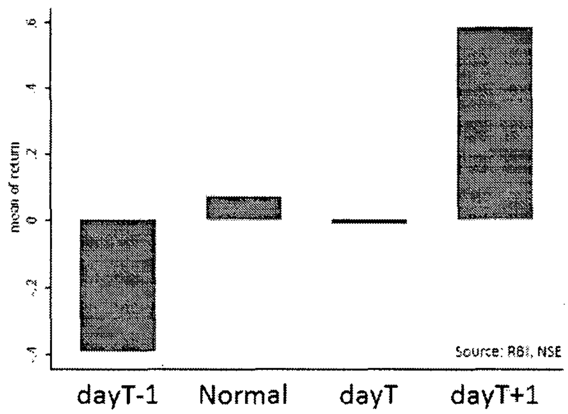


Figure 4.3: Contractionary Policy Event

the run-up towards policy, which is corrected for in the coming days. High negative returns are witnessed during the day before a contractionary policy announcement (-0.29%). Compared to this the mean return on the day of a contractionary policy announcement is smaller (-0.12%). Like in expansionary policy, we again witness a reversal of sign after the day of announcement (0.18%). A graphical representation of the two events are given in figures 4.2 and 4.3.

The high (low) returns prior to an expansionary (contractionary) policy announcement would imply that markets anticipate the policy stance.

Figure 4.4: Mean Returns of Contractionary Policy Events After 2006



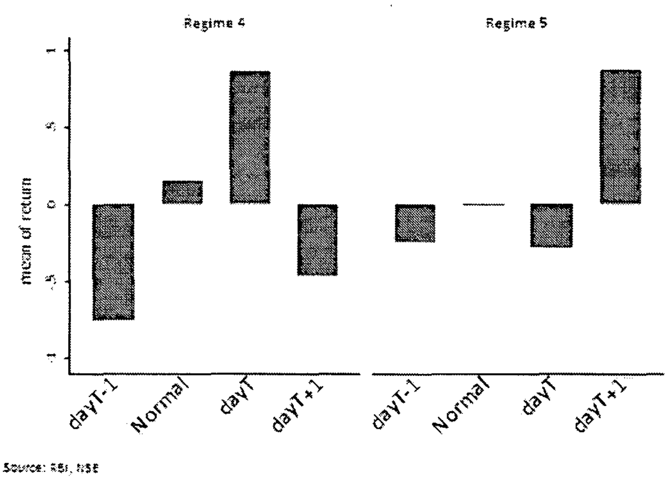
Then rational traders might be taking a trading strategy in which they go long (short) in anticipation of an expansionary (contractionary) policy announcement. And sell (buy) the day after an expansionary (contractionary) policy announcement is made. The return behavior seen here would imply that markets are not reacting to stale information and is probably semi–strong efficient for the information set of monetary policy announcements.

4.3.1 Impact Across Structural Breaks

Weak form efficiency is a precondition for testing semi-strong efficiency. In Chapter§3 we saw that markets are weak form efficient only in the third and fourth structural breaks, beginning in June 2003. Therefore, we test for semi-strong efficiency for monetary policy announcements after this period only. We have a total of 21 events during this period (see table 4.1), of which 20 pertains to contractionary policy event and only 1 corresponding to an expansionary policy event. Therefore, we examine only the impact of contractionary policy beginning from the fourth regime.

Aggregating the two regimes, we see that during a contractionary policy event, there are highly negative mean daily returns before the announcement; near zero returns on the day of announcement and excessive positive returns the day after. That is, we see a reversal in sign

Figure 4.5: Mean Returns of Contractionary Policy Event Across Regimes 4 and 5



(see figure 4.4). For a much disaggregated analysis, we separate the two regimes and examine the event. Graphical summary of this is provided in figure 4.5. Though we do see a reversal in sign, the pattern is quite different. In regime4, we see high negative returns on the day before announcement and high positive returns on the day of announcement. But, immediately the day after, the mean returns revert in sign to negative. Whereas in the case of regime4, negative returns are observed on $t-1$ and t. But, turns positive the day after the announcement.

Is the reversal in sign just a random occurrence, or is it consistent across all the observations? Looking at table 4.3 we can see that only 2 out of 5 observations had a reversal in sign from positive to negative between t and $t+1$in the third regime. In the case of the fifth regime, only 6 out 14 observations had a reversal in sign from negative to positive. Which implies that there is a high possibility that our estimator of mean could be highly influenced by extreme values or size of the observation, than by systematic patterns. To test for this, we undertake nonparametric tests. The procedure for conducting nonparametric tests is detailed in the next section.

Table 4.3: Returns During Contractionary Policy: Regimes 4 and 5[a]

Regime	$(t-1)_{cont}$	$(t)_{cont}$	$(t+1)_{cont}$
4		1.19	0.39
4	-1.27	1.35	0.16
4	-1.11	0.30	-2.02
4	-2.02	0.97	-0.40
4	-0.58	0.83	1.11
5	-2.65	-4.87	5.08
5	1.38	1.81	2.26
5	0.79	-0.67	0.61
5	0.37	0.00	-0.01
5	-0.56	-1.02	1.33
5	-3.13	-0.34	0.06
5	-0.12	1.98	-4.12
5	3.51	-0.63	0.54
5	0.16	1.44	1.57
5	-0.43	2.06	-0.57
5	-1.14	1.64	0.35
5	-1.88	-1.78	1.46
5	0.47	-3.34	2.91
5	-3.34	2.91	0.45

[a] Computed statistics
[b] Policy data from RBI
[c] Returns computed from NSE price data

4 Nonparametric Analysis

Owing to the small sample size problem and non-normality of the distribution, we use nonparametric techniques to test our various hypothesis that has emerged from exploratory data analysis. These hypothesis are:

1. Returns during an expansionary policy event is greater than a contractionary policy

2. During an expansionary policy event, returns are highest on day $t-1$ compared to $t+1$

3. During a contractionary policy event, returns are lowest on day $t-1$ compared to $t+1$

4. There is a reversal in sign after the day of announcement during a contractionary policy event

Nonparametric tests are primarily designed to check for consistency in the patterns of observation, when it is difficult to make a scientific judgment regarding it. They are more concerned about the direction of the observation than its size. Here we use Wilcoxon rank sum (Mann-Whitney) test amd Wilcoxon signed rank test. We first explain the procedure of Wilcoxon signed rank test. The approach for testing it is as follows: We take D_i as

$$D_i = r_{t-1} - r_{t+1}$$

and take as our model

$$D_i = \theta + e_t$$

where e_t is the unobservable random variable and our parameter of interest θ is the unknown 'information effect' on the returns, due to the new information (Hollander and Wolfe, 1973). We test the null hypothesis:

$$H_0 : \theta = 0$$

To test, we take the absolute differences $|D_1|, |D_2|, ..., |D_n|$, where n is the number of policy announcement. Then rank this from least to greatest.

Define ψ as

$$D_i > 0 \Rightarrow \psi_i = 1$$
$$D_i < 0 \Rightarrow \psi_i = 0$$

Our test statistic is defined as:

$$T^+ = \sum_{i=1}^{n} R_i \psi_i$$

where R_i denotes the rank of $|D_i|$.

T^+ is known as the positive signed rank of D_i.

$$D_i > 0 \Rightarrow T^+ = R_i$$
$$D_i < 0 \Rightarrow T^+ = 0$$

Therefore, T^+ is the sum of positive signed ranks (Hollander and Wolfe, 1973).

For testing the H_0 against the alternative $\theta > 0$, at significance level α; Reject H_0 if

$$T^+ \geq t(\alpha, n)$$

Therefore, the null hypothesis we test is that there are no differences in returns and any we see is just random, since difference D_i is equal to

$$D_i = \theta + e_t$$

We can also test the null hypothesis that two population locations are the same using Wilcoxon rank sum test.

Suppose our sample 1 consists of returns during $t-1$ and sample 2 consists of returns during $t+1$. We merge the two samples together and then rank it. Let us denote the sum of ranks for sample 1 as R_1, which we can take as our test statistic R. A small value of R indicates that most of the smaller observations are in sample 1, and larger observations in sample 2. But we need to prove that R is small. If our null is true then it implies that each possible ranking is equally likely. For example, assume that there are 3 observations in each of the two samples. So we have altogether 6 observations which can be arranged in ${}^{6}C_3$ ways, i.e., 20 different ways. From this a sampling distribution of R can be drawn. We can compute the probability of each rank appearing in the sampling distribution to be as $Freq/{}^{n}C_r$. For sample sizes greater than 10, sampling distribution of R can be approximated to a normal distribution (Keller, 2001). The test statistic is given by:

$$Z = \frac{R - E(R)}{\sigma_R}$$

Where,

$$E(R) = \frac{n_1(n_1 + n_2 + 1)}{2}$$

$$\sigma_R = \sqrt{n_1 n_2 (n_1 + n_2 + 1) 12}$$

Hypothesis 1: Returns during an expansionary policy event is greater than a contractionary policy :

We use Wilcoxon rank sum test to test the hypothesis:

$$H_0 : Return_{Exp} = Return_{Cont}$$
$$H_1 : Return_{Exp} \neq Return_{Cont}$$

$Return_{exp}$ = Returns during expansionary policy event
$Return_{cont}$ = Returns during contractionary policy event

Results:

Policy	Obs	Rank sum	Expected
Contractionary	70	5128	5390
Expansionary	83	6653	6391
Total	153	11781	11781
variance	74561.67		
Z	-0.959		
$Prob > \|z\|$	0.3373		

Test statistic $Z = -0.959$ is insignificant at 5% significance level with a p-value of 0.3373. Therefore, we do not reject the null hypothesis.

Hypothesis 2: During an expansionary policy event, returns are highest on day $t-1$ compared to $t+1$:

Using signed rank test we test

$$H_0 : Exp_{t-1} = Exp_{t+1}$$
$$H_1 : Exp_{t-1} \neq Exp_{t+1}$$

Exp_{t-1} = Returns during the day before an expansionary policy announcement

Exp_{t+1} = Returns during the day after an expansionary policy announcement

Results:

Sign	obs	Rank sum	Expected
Positive	15	246	248
Negative	16	250	248
All	31	496	496
Variance	2604		
Z	-0.039		
$Prob > z$	0.9687		

The test statistic $Z = -0.039$ with a p-value of 0.9687 is insignificant at 5% significance level. We do not reject the H_0

Hypothesis 3: During a contractionary policy event, return are lowest on day $t-1$ compared to $t+1$:

Using signed rank test we test

$$H_0 : Cont_{t-1} = Cont_{t+1}$$
$$H_1 : Cont_{t-1} \neq Cont_{t+1}$$

$Cont_{t-1}$ = Returns during the day before contractionary policy announcement

$Cont_{t+1}$ = Returns during the day after contractionary policy announcement

Results:

Sign	Obs	Rank sum	Expected
Positive	11	122	162.5
Negative	14	203	162.5
All	25	325	325
variance	1381		
Z	-1.090		
$Prob > z$	0.275		

We do not reject the null hypothesis since the Z-statistic -1.90 is insignificant at 5% significance level.

Hypothesis 4: There is a reversal in sign during a contactionary policy event :

To test this hypothesis we use a modified version of Fisher's sign test. For this, we define ψ_i as 1 if we see a reversal in sign after the day of announcement during regime4. That is, $\psi_i = 1$ if $r_t > 0$ but $r_{t+1} < 0$.

We define B as

$$B = \sum_{i=1}^{n} \psi_i$$

The test statistic B* is defined as:

$$B* = \frac{B - (n/2)}{(n/4)^{1/2}}$$

Reject null hypothesis of no reversal in sign if $B* \geq Z_{\alpha/2}$

The computed $B* = -0.8$. Therefore we do not reject the null hypothesis that there is no reversal in sign.

Similarly, the test was repeated for regime 5. But, we redefined ψ_i as $\psi_i = 1$ if $r_t < 0$ but $r_{t+1} > 0$.

For regime 5, $B* = -0.5714$. Therefore, we do not reject the null hypothesis of no reversal in sign.

Recap : Results from nonparametric tests reveal that there is no systematic difference across the day of events or policy. The results also imply that monetary policy do not affect have any systematic impact immediately in the Indian stock market.

4.5 Summary

Financial markets are at the core of monetary transmission mechanism. Therefore, we expect monetary policy announcements to have significant impact on the stock market. The focus here has been to see how the markets react to a widely known event, having an economy wide impact. In an efficient market, the prices react instantly to a new information. A market riding on stale information is informationally inefficient. In the case of monetary policy announcement, markets anticipate an announcement to be forthcoming and, ideally it should be reacting to the unexpected component in the announcement. Any overreaction or under-reaction will be corrected following the information about the unexpected component.

With only exploratory data analysis it would have made us conclude that the pattern exhibited by returns is indicative that the markets anticipate the policy stance in advance and is reacting accordingly, since we see negative (positive) excess returns before an contractionary (expansionary) policy announcement. One might have had the evidence of returns reverting in sign the day after an announcement, indicating that markets overreact on and prior to announcement which is adjusted for in the coming days, implying that the market do not continue to ride in the direction of stale information. Such a pattern could be in the direction of semi–strong efficiency. Traders who anticipate the direction of, say, contractionary policy announcement will short–sell before the announcement expecting the market to react downwards following a contractionary policy announcement. If the markets moves down further after the announcement then buying back the shares after the event would have been a profitable trading strategy . Instead, the buying pressure on the market after the event gives a fillip to the prices (which we see as positive returns). A trader reaching late in the market to trade in the direction of the policy would probably find a market moving against his expectation. This can be in line with the semi-strong efficiency of the Efficient Markets Hypothesis.

But, parametric inferences can be highly misleading. Therefore, our exploratory data analysis was tested using nonparametric tests. Nonparametric tests have the advantage that they are distribution free and can be applied to small samples. The nonparametric tests we used – Wilcoxon rank sum test, Wilcoxon signed rank test and Fishers sign test have the added advantage that they are primarily testing for consistency in behaviour. Unlike the arithmetic average, they are not influenced by the size of single observation. Rather they are more concerned with the direction.

The nonparametric tests rejected any consistent behaviour across the periods of policy and type of policy. That is, it rejected any systematic difference in the return behaviour between expansionary and contractionary policy, as well as the days corresponding to the policy announcement event. The contradictory results with exploratory data analysis could be due to distributional properties of returns. Being a Paretian distribution, it is possible that we observe large changes during short periods of time. Therefore, there will be a few large values of returns which can severely influence the direction of the parameters. Together, the results would imply that there is no consistent, systematic effect of monetary policy announcements immediately on the Indian stock market. This makes our conclusion on semi-strong efficiency difficult for several reasons. First, it could be that market is too noisy to separate out the impacts of specific events. But a highly noisy market is inefficient. Second, it could be that each policy event have differing impacts on expectations. That is, the impact on expectations of a contractionary policy to prick an asset price bubble will be different from one which is directed at controlling rising inflation. If that is the case, one will not see any consistent patterns through which monetary policy effects stock market.

Chapter 5

Conclusion

In the Neoclassical trading, a highly competitive financial market is expected to behave efficiently. When it is so, the current price of financial assets will discount all available information quickly and correctly. If the current prices reflect correct prices then there will be no undervalued or overvalued stocks in the market. There will be little possibility of generating excess returns over the market returns by analysing current information. The observed price changes are due to the arrival of new information or by the action of uninformed traders creating 'noise' in the market. The new information arrival is expected to arise independently and randomly. So do the price changes. With regard to noise in the market, each individual's valuation of the intrinsic value of the assets is independent of each other and the noise arises due to the uncertainty or disagreement concerning the intrinsic value. But such disequilibrium created by noisy traders is expected to be white noise and simply temporary aberrations.

For empirical analysis of efficiency, it can be classified into three based on the information set. When forecasting is futile or generating excess returns with the analysis of the information set of historical data is futile, then the market is weak-form efficient. The testing procedure is also called the test for predictability of returns. When the information set pertains to all published and publicly available information, then it is semi-strong efficient. Tests for semi-strong efficiency perform what is called an event study. Finally, when the information set contains all information - public as well as private, such that even insider trading cannot generate excess returns, market is strong form efficient. Tests for strong form efficiency fall within the tests for private information.

With this theoretical backdrop our research examined the behaviour of stock market prices in India and the information efficiency of the stock markets. With regard to the former, we were interested in identifying its structural changes, and understanding the returns generating process through this period. In examining the objective of information efficiency, we tested for weak form efficiency and semi-strong form of efficiency. With regard to weak form efficiency we tried to see whether the observed price and return behaviour fit the theoretical ideal, and whether this behaviour has undergone changes over time. For testing semi-strong efficiency, we were concerned with the question of how the stock market reacts to the arrival of information which has an economy-wide impact. This information, for us, was the event of Reserve Bank of India's monetary policy announcements. The principle data we use is the daily trading data of S&P CNX Nifty - the market index of National Stock Exchange of India, for the period January 1991 to October 2008.

The study began by examining the structural changes in the market prices. For this Bai-Perron's test procedure for multiple structural changes was employed. The technique is a great improvement over the conventional Chow-test. The latter tests for statistically significant differences in parameters across periods suspected of a break date, where the break-dates are provided exogenously i.e., it is assigned by the researcher. Therefore, the family of Chow tests do not identify a structural break; instead it only tests the validity of a suspected break. In contrast, Bai-Perron method allows for simultaneous estimation of unknown multiple breaks. Employing this test procedure we identified four structural structural breaks, implying that there are five regimes which the price series has went through. They are: 02Jan'91 to 07Dec'94, 08Dec'94 to 02Jul'99, 03Jul'99 to 25Jun'03, 26Jun'03 to 24Jan'06, and 25Jan'06 to 23Oct'08. We were able to see considerable differences in the mean daily returns were observed across these periods.

The daily returns data was explored for these periods to identify its distribution. Exploratory graphical analysis using histogram, box-plots and normal probability plots pointed out that the returns do not follow a normal distribution. On computing the probability contained within success standard deviations of the return distribution, it was found that it is closer to a stable Paretian distribution. If it would have been a normal distribution, then we expect the individual price changes to be smaller compared to the total change, and the path of price change will be continuous with a finite population and sample variance. Whereas, the observed paretian distribution has the feature that the size of the total will more than likely to be the result of a few large changes that took place during much shorter sub-periods, making the path of price changes dis-continuous. This gives it the property of infinite population variance - i.e., population variance doe not exist. So, sample variance will show extremely erratic behaviour even for very large samples. This implies that measures with sample variance are not very meaningful.

These findings have major implications for our tests for efficiency. Weak form efficiency implies that price changes would be random and independent of previous price changes. Testing for these would form the tests for weak form efficiency. Since, the distribution of returns is not normal, but Paretian, we resort to non-parametric techniques. Runs-test is a non-parametric technique which tests whether a certain series is randomly ordered. Runs test is performed for the returns series, both for the whole series as well across the period of structural breaks. The runs-test rejected the hypothesis of random order for all the series except for the last two regimes of 26Jun'03 to 24Jan'06, and 25Jan'06 to 23Oct'08. Thus, we were able to see that there is significant changes in return generating process over the periods of structural breaks, But, overall we would conclude that market has begun to move towards the theoretical ideal defined for weak form efficiency. These are significant results compared to the previous studies on weak form efficiency in India. These studies were primarily focused at providing a verdict on efficiency, but the dynamics involved in it was little explored.

Weak-form efficiency was again examined by testing for the presence of anomalies in the returns behaviour which would make it predictable. One such anomaly to market efficiency is the presence of seasonality in returns, also known as the month-of-the-year effect. In an efficient market such anomalies do not persists due to the action of arbitrageurs. But, studies have documented the presence of seasonality in the Indian markets. This issue was examined by first conducting an exploratory data analysis and then tested using Spearman's rank correlation coefficient, a nonparametric technique, which tested whether seasonality in returns persists across time. But, we were not able to mine any seasonality of returns. We concluded that chapter by pointing out that such exercises suffer from data snooping bias and it is possible that one may find significant relations if the data is analysed with sufficient intensity.

Finally, the issue of semi-strong efficiency was examined. Semi-strong efficiency relates to the hypothesis that all the available information, particularly news and published information, will be reflected in the prices quickly and correctly such that it will not be possible to generate excess returns with that information. This was examined for the information set of monetary policy announcements, since monetary policy being one of the major factors which affect the financial market activity directly. All the monetary policy announcements which brought a change in the bank rate, repo rate and CRR during the period 1996 to 2008 were examined. Altogether we analyse 57 policy announcements. The dates of policy announcements were compiled from various RBI annual reports. We examined only the movements in the index, since it is expected to reflect only economy-wide information which has an impact across the firms. The event window is three days – the day before an announcement, the announcement date and the day after the announcement. The event was further classified into events of expansionary policy and contractionary policy. Since weak-form efficiency being a precondition for semi-strong efficiency, analysis across structural breaks was conducted only for the last two regimes beginning June 2003, besides analysing the aggregate data set. The impact of the announcements during the event window was first examined through exploratory data analysis (EDA) and then statistically tested using various nonparametric techniques such as Wilcoxon rank sum (Mann-Whitney) test, Wilcoxon signed rank test and Fishers sign test, which rejected all of our inferences from exploratory data analysis.

EDA primarily examined the mean daily returns. It found excessive positive returns during an expansionary policy event and excessive negative returns during a contractionary policy event. During an expansionary policy event, the day before the announcement had high excessive positive mean returns, followed by negative mean returns on the day of announcement and then reverting to positive returns the day after. In the case of a contractionary policy event, the day before the announcement had excessive mean negative returns and the day after the announcement had high positive mean returns. The period after the third structural break, i.e., since the fourth regime there were 21 events, of which 20 corresponds to a contractionary policy announcement. During the period, high negative mean returns were witnessed for the day before contractionary policy announcements. The mean returns were seen to revert in sign after the announcement. Between fourth and fifth regimes, we saw reversal in the mean daily returns but the pattern being different between the two. All these observations were tested using nonparametric statistical techniques. In the process we saw that, in fact, there was no 'consistent' pattern in the way returns are arranged during the event of monetary policy announcements. The tests rejected consistent presence of all our observations from EDA without exception. This is indicative of the fact that there are a few observations which pull the mean towards them. Large changes during short periods of time is a characteristic of Paretian distribution. In short, the results point out that there are no systematic, consistent impact of monetary policy announcements immediately on the stock market. This can happen for several reasons. It could be that market is too noisy to separate out the impacts of specific events. Or, it could be that each policy event have differing impacts on expectations. That is, the impact on expectations of a contractionary policy to prick an asset price bubble will be different from one which is directed at controlling rising inflation. If that is the case, one will not see any consistent patterns through which monetary policy effects stock market. This makes a conclusion about semi-strong efficiency a difficult proposition.

Implications: The findings have important implications for investors and policy makers. For investors, the finding that the returns follow a paretian distribution holds great significance. Conventional risk analysis using standard deviation might not reflect the true picture of risk. There is a higher probability of extreme events than is predicted by risk models based on normal distribution. If the markets are efficient, then the best trading strategy would be to buy and hold Index funds, since no other trading strategy can give returns above the market returns. Besides, an index fund would give a fair level of diversification. The investor also needs to take particular care during the times of major events such as policy announcement, budgets, elections etc. The markets are seen to overreact and with much more sophistication which naive trading strategies cannot capture, making predictions difficult. This can be seen from our results of semi strong efficiency. Also, investors should keep away from trying for a 'quick-buck' with popular anomalies. We have seen that many of the popular anomalies are not a consistent occurrence or do not actually exists, but exists mostly as a statistical curiosity probably emerging out of excessive data analysis. In this light investor education, which is already a policy agenda, should be taken up with more vigor by the respective authorities. It is also necessary that investor education should move beyond simple financial literacy and should highlight the huge risks involved if the market is treated as an avenue for making quick money, as against an institution facilitating mobilisation of savings and investment.

Besides these, our research has opened up new areas of further research. An interesting question that arises is – what made the Indian market weak form efficient in the recent period? Though one can think of many hypothesis such as advancements in technology; improved growth rates in India facilitating channeling of more funds to the market; increase in the number of institutional investors; or their approach to investing....the list can continue, but only a systematic research can uncover the true nature of these factors. Our results with regard to impact of monetary policy announcements could be quite startling to many. The results in no way suggest that monetary policy do not affect the financial market. Instead, what the finding implies is that immediate impact of monetary policy *announcement* on the market is seen to be random rather than systematic or consistent across all the announcements. But, our study has not separated out the differences in the instrument used, their levels and its consequent impact. This we intend to take up as an issue of further research.

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