Dynamics of Market Efficiency: An Empirical Examination of the Adaptive Market Hypothesis in the Indian Equity Market

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By

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DECLARATION

I, Shet Khemraj Alias Sangam, hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or in full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau.
Date : 21-11-2025

Khemraj Alias Sangam Shet

CERTIFICATE

I hereby certify that the above declaration made by the candidate, Shet Khemraj Alias Sangam, is true to the best of my knowledge and the thesis work was carried out under my supervision and guidance.

Prof. Y.V. Reddy
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List of Abbreviations

Abbreviations	Full form
0x	ZRX Token
ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
AMH	Adaptive Market Hypothesis
AR	Autoregressive
BIST100	Borsa Istanbul 100
BRIC	Brazil, Russia, India, China
BSE	Bombay Stock Exchange
BsFSI	Banking Sector Financial Soundness Indicator
CAGR	Computed Annual Growth Rate
CSV	Comma-Separated Values
DJIA	Dow Jones Industrial Average
DL	Dominguez Lobato
EMH	Efficient Market Hypothesis
GARCH M	Generalised Autoregressive Conditional Heteroskedasticity in Mean
GS	Generalised Spectral
HMM	Hidden Markov Model
LOESS	Locally Estimated Scatterplot Smoothing
LPG	Liberalisation, Privatisation, Globalisation
MDH	Martingale Difference Hypothesis
MFDFA	MultiFractal Detrended Fluctuation Analysis
NASDAQ	National Association of Securities Dealers Automated Quotations
NDA	National Democratic Alliance
NSE	National Stock Exchange
RWH	Random Walk Hypothesis
SBIC	Schwarz Bayesian Information Criterion
SD	Standard Deviation
SMM	Studentized Maximum Modulus
STL	Seasonal and Trend Decomposition

TOPIX	Tokyo Stock Price Index
TSE2	Tokyo Stock Exchange Second
UPA	United Progressive Alliance
VR	Variance Ratio
WTI	Western Texas Instrument

Abstract

The Efficient Market Hypothesis (EMH) argues that stock prices fully reflect available information, leaving little room for predictability in returns. However, growing empirical evidence shows that financial markets do not remain uniformly efficient across time; instead, they evolve in response to structural shifts, crises, regulatory changes, and behavioural factors. In this context, the Adaptive Market Hypothesis (AMH) provides a dynamic framework to study how efficiency strengthens or weakens under varying market conditions. This study investigates the evolving nature of market efficiency and return predictability in the Indian equity market using the BSE Sensex as the focal index. The analysis spans daily data from 1988 to 2024, segmented into meaningful sub-periods based on parliamentary election cycles, periods of heightened political uncertainty, and major economic events.

Using daily data for the full sample period and carefully selected subsamples representing different market regimes. First, we examine the time-varying return predictability of the BSE Sensex using a battery of variance-ratio tests, including the Lo–MacKinlay Variance Ratio Test, the Chow–Denning Multiple Variance Ratio Test, and Wright's (2000) Rank and Sign Tests. These methods are applied to the full sample and to subsamples classified by parliamentary election periods. The findings reveal that the full sample strongly rejects the random walk hypothesis, indicating persistent predictability and weak-form inefficiency. Interestingly, several election-year subsamples exhibit random-walk behaviour, suggesting temporary improvements in efficiency when political uncertainty is high. However, the period preceding the 16th Parliamentary Election, which culminated in a significant regime change, displays strong predictability. This behaviour differs from earlier elections and may reflect the expanding influence of social media and rapid information diffusion. Across crisis-related subsamples—including the 2008 financial crisis and the post-COVID period—the Sensex consistently exhibits similar return dynamics. We also assess the evolving nature of market efficiency through rolling-window Dominguez–Lobato (DL) and Generalised Spectral (GS) tests. These are applied using a 100-day rolling period across the full sample and across eight election-based windows spanning four major election cycles. The results show that market efficiency is not constant but evolves over time, offering strong empirical support for the Adaptive Market Hypothesis (AMH). Inefficiency spikes during phases such as the 11th Parliamentary Election, suggesting heightened predictability and opportunities for excess returns. Even in more recent elections, such as the 16th and 17th, inefficiencies

persist, implying that easier access to information has not fully translated into improved market efficiency.

As part of the second objective, we also implement Multifractal Detrended Fluctuation Analysis (MF-DFA) to measure long-range dependence and the degree of market efficiency. MF-DFA results indicate multifractality and time-varying long memory in Sensex returns, which vary significantly across election cycles and market regimes, further validating the adaptive behaviour of the market.

Third, to quantify time-varying inefficiency more precisely, we estimate a time-varying AR(1) model within a State Space framework using the Kalman Filter. The evolution of the AR(1) coefficient captures dynamic shifts in predictability. The results confirm that inefficiency intensifies during periods of elevated uncertainty, political transitions, and economic stress, while it weakens during stable market conditions. The AR(1)-based inefficiency patterns align closely with the results from the variance-ratio tests, DL/GS rolling tests, and MF-DFA measures, collectively reinforcing the evidence for AMH.

Overall, the study demonstrates that market efficiency in the Indian stock market is not static but exhibits adaptive and cyclical properties, shaped by political events, economic conditions, and investor behaviour. These findings have significant implications for traders, arbitrageurs, and policymakers by demonstrating how and when predictable structures emerge in stock prices and how efficiency fluctuates with evolving market environments.

Keywords

Adaptive Market Hypothesis, Efficient Market Hypothesis, Evolution, Stock Market, Predictability, MFDFA.

Chapter I

Introduction

This chapter provides an overview of the central research theme explored in the thesis, emphasising the significance and relevance of the present study. Defines the scope of the study and explains its importance in the current context. It also includes a detailed review of the prior literature on the topic, organised according to each research objective, to facilitate the identification of research gaps. From these research gaps, the research questions and objectives are subsequently developed. The chapter concluded by describing the overall organisation of the thesis, serving as a guide to the subsequent chapters.

1.1 Introduction

The growth of the Indian stock market has been phenomenal since 1992, with a CAGR of around 14.12% CAGR[a1]. One of the premises for the market to work is that it must be efficient. Efficiency refers to how well the market reflects available information quickly and accurately in stock prices. In an organised market, price movements are random and are expected to follow the efficient market hypothesis, as formulated by Fama (1970). The Efficient Market Hypothesis explains this by classifying the market into three forms: the weak form, the semi-strong form, and the strong form. Efficient Market Hypothesis has been around since the 1965s when Paul Samuelson proposed in his article titled "Proof That Properly Anticipated Price Fluctuates Randomly". Eugene Fama (1970) and (2004, 2005) operationalised it as we use it now. It says that stock prices are always traded at a fair price, leaving no scope for gains from the purchase and sale of overpriced or underpriced securities; i.e., it means the market reflects all information and expectations of market participants. However, in real life, it does not hold, as from time to time imperfections in the market have made returns predictable. Also, there was no need to manage the portfolio if predictability was not possible, which it is not. The theory classifies the market into three forms: weak, semi-strong, and strong form. The weak form says that all past information is reflected; the semi-strong form says that past and publicly available information are reflected; the strong form says that past, public, and private information are reflected (Roberts, 1967). A substantial number of studies examined the three forms of market efficiency, yielding contradictory, controversial results scattered across markets worldwide. Most researchers reported weak-form efficiency (Thomas, 2010)and (Asha et al., 2010). Mishra et al. (2012) and Mishra & Pradhan (2009) reported partial weak-form efficiency in the Indian stock market. (Charles & Darné, 2009) have explored weak-form efficiency in the Brent and WTI crude oil markets and the relationship between efficiency and changes in regulation, using new variance-ratio tests. The results suggest that Brent crude oil prices are weak-form efficient, whereas the WTI crude oil market appears inefficient during the 1994–2008 sub-period. At the same time, other researchers, such as Chovancova & Arendas (2015), show that BRIC share markets, although weak-form inefficient in the long term, exhibit alternating periods of weak-form efficiency and weak-form inefficiency over shorter time periods. Further, there is still no consensus among various researchers. Apart from this, Andrew Lo (2004, 2005) has listed various other inconsistencies and structural ambiguities of the EMH.

Lo (2004, 2005) suggested an Adaptive Market Hypothesis to counter the contradictory claims of EMH and to provide concise explanations for these conflicting results. Lo (2004, 2005) provided an evolutionary approach in which the market continually evolves and adapts to a constantly changing environment, switching from efficiency to inefficiency. AMH focuses on the behaviour of changing market conditions(Kılıç, 2020). Lo (2005) describes the financial market as an evolutionary system in which competition, reproduction, and natural selection affect the market's efficiency and, thereby, the rise and fall of profitability. According to AMH, market participants behave differently across market conditions, leading to varying degrees of efficiency in different market environments, depending on economic, social, and political events (Lo, 2004).

We study the Adaptive Market Hypothesis in the context of the Indian stock market, one of the world's emerging, fastest-growing markets alongside China. Few previous studies have examined AMH in relation to time-varying return predictability of the Indian stock market, such as those by (Hiremath & Kumari, 2014a, 2014b; Hiremath & Narayan, 2016; Patra & Hiremath, 2022a). Further, literature on the information efficiency of the Indian Stock market from an Adaptive Market Hypothesis perspective is limited, given its status as one of the fastest-developing markets. Political ideologies often influence stock returns (Bonaparte, 2025), and returns tend to be more predictable during periods of political uncertainty (Kim et al., 2011). So, analysing parliamentary elections from the AMH perspective can provide valuable insights into market behaviour.

1.2 Need for the study

We classify the need for the study into three parts.

1) There is a need to study the efficiency of Indian stock indices from an event perspective, as none of the studies in the Indian context has done so, though Okorie & Lin (2021) studied the pre- and post-COVID efficiency; moreover, none have studied AMH from a standalone, repetitive event (Parliamentary election) perspective.
2) Secondly, there is also a need to know how strongly and quickly the market reflects all available information. However, some studies have studied the same by using an entropy approach in the context of India, as perfect information efficiency depends on the degree of efficiency ratio in each window, as pointed out by (Bhuyan et al., 2020). We use the MFDFA methodology to assess the degree of efficiency, as it better captures the scaling behaviour and complexity of the time series.
3) Two approaches are used to study AMH. The first approach uses a time-varying model to measure market efficiency, while the second approach utilises various statistical methods, including the moving-window method (Noda, 2016), to investigate it. To the best of our knowledge, both approaches are widely used to study market efficiency, and excluding market inefficiencies and detecting them have been crucial objectives for trading practitioners (Khuntia & Pattanayak, 2020). However, as Lo argues, both period efficiency and inefficiency exist in a market.

1.3 Scope of the Study

In this study, we examine the evolution of market efficiency in the Indian equity market within the AMH framework, with special emphasis on the BSE Sensex. The scope of the study is limited to the analysis of the broad market index and its subsamples across different time periods and market conditions. Primarily, the scope of our research involves analysing the long-term and short-term efficiency behaviour of the BSE Sensex. Using time-varying econometric models such as time-varying AR(1), Kalman filtering, rolling-window tests, and long-memory measures (Hurst exponent, MF-DFA), the study evaluates whether the Sensex exhibits periods of predictability and unpredictability. This allows us to assess whether the efficiency of the Indian market evolves in response to changing market conditions, consistent with AMH. To better understand the market's adaptive behaviour, the study analyses the sub-indices of the BSE Sensex. These subsamples are created based on the parliamentary election. Analysing sub-samples helps examine how efficiency changes across different time periods, whether efficiency varies, and how market conditions influence predictability.

We also apply the multifractal Detrended Fluctuation Analysis (MF-DFA) technique to estimate the Hurst exponent and Multifractal spectrum, thereby quantifying the degree and strength of long-range dependence, which reflects the degree of efficiency in the market. Further, a time-varying AR(1) model estimated through the state space framework and Kalman filter is used to capture evolving predictability in returns. The time-varying AR coefficient serves as a direct measure of time-varying inefficiency.

1.4 Significance of the Study

In this study, we examine the Adaptive Market Hypothesis in the Indian stock market. India, which is one of the emerging and fastest-growing markets, is besides China. Further, since it is not as developed as the US and European markets in some respects but is comparable in terms of liquidity and capitalisation, it provides ample opportunity to study other structural changes and outliers that will have an Impact and be incorporated as it matures. The study also becomes essential as, in the last few years, with the smartphone revolution, access to cheap data packs, and the entry of discount brokers like Zerodha and Upstox into the Indian market, the number of retail investors is increasing, necessitating a study of their Impact on the efficiency of the market. As one of the largest democracies in the world, elections play a significant role in shaping a country's business environment and economic policies. It becomes imperative to examine the impact of the parliamentary election on the stock market. As the Indian market evolves rapidly, there is a need to contribute to the literature on AMH.

1.5 Literature Review

Stock market efficiency has been a highly debatable topic since the 1960s. First, the Efficient Market Hypothesis was used to characterise the efficiency in the stock market. Later, the Adaptive Market Hypothesis. This section provides insight into the existing literature on the central theme of this study —i.e., Adaptive Market Hypothesis (AMH), Political Risk (Elections) and the stock market, Subsamples, the time-varying return predictability, and its consistency with the AMH of the primary Indian stock index, the information efficiency of the Indian Stock Market, and the time-varying inefficiency of the Indian Stock Market.

1.5.1 Adaptive Market Hypothesis

Stock market efficiency has been a highly debatable topic since the 1960s. First, the Efficient Market Hypothesis was used to characterise the efficiency in the stock market. Later, the Adaptive Market Hypothesis. Due to the contradictory, controversial nature of the Efficient Market Hypothesis, Lo (2004) proposed a novel approach to reconcile the two opposing schools of thought: the adaptive market hypothesis (AMH). Lo (2004) describes the market in terms of principles drawn from a biological perspective. Lo argues that market efficiency under AMH changes in response to market conditions and continues to evolve as the market evolves. Both periods of market efficiency and inefficiency are prevalent at various points in time. They adapt to environmental changes influenced by events and structural shifts. This evolution affects market shifts. Unlike the Efficient Market Hypothesis, which assumes constant market efficiency, AMH posits that efficiency varies. At times, markets may be more efficient and at other times less so, influenced by various factors including behavioural biases. The level of informational efficiency under AMH also depends on market participants' ability to adapt to changing market conditions (Dhankar & Shankar, 2016). In recent years, AMH literature has received significant academic interest. Several studies have examined AMH in relation to the stock market and Bitcoin. Lim and Brooks (2006) studied emerging and developed stock markets by applying rolling portmanteau bicorrelation test statistics to a sample; the results revealed that market efficiency cyclically varies over time. Ito & Sugiyama (2009) studied time-varying market efficiency and found that markets are simultaneously efficient and inefficient at times. There are studies studying momentum and contrarian profit to identify the existence of the adaptive market hypothesis (Akhter & Yong, 2019), moving average strategies (Todea et al., 2009), calendar anomalies (Urquhart & McGroarty, 2014; Xiong et al., 2018) (Al-Khazali & Mirzaei, 2017), and moving average rule (Urquhart et al., 2015). Urquhart & Hudson (2013) studied how the independence of stock returns has behaved over time, providing evidence of the market being adaptive. Charles et al. (2012) studied the predictability of foreign exchange rates and found that they are predictable. Boya (2019) examined the degree of market efficiency in the French stock market and tested whether the results from the efficient market hypothesis and the adaptive market hypothesis were consistent with AMH. Similarly, Noda (2016) examined the degree of market efficiency in the Japanese stock market, namely the TOPIX and TSE2 indices, using a time-varying approach. Both markets reflect changing efficiency. In comparison, TOPIX was more efficient than TSE2 and supports AMH. Studies such as those by Kyei et al. (2023) assessed the effect of commodity prices on the BsFSI Indicator under market conditions (bullish, normal, and bearish) using quantile regression and the causality-in-quantiles estimation technique. They noticed an asymmetrical relationship between the commodity (cocoa, gold and crude oil) and the BsFSI indicator. A prediction is possible given market conditions, and overall, the market confirms AMH. The relative efficiency of AMH across different crude oil benchmarks — namely, WTI, Brent, and Dubai crude — was studied by Varghese & Madhavan (2022). They employed rolling Hurst exponent analysis. Followed by non-parametric tests to check for homogeneity in the degree of efficiency. The crude oil market was found to be efficient for most of the study period, followed by a short span of inefficiency. Relatively, WTI was found to be the most efficient, followed by Brent and Dubai crude. Khuntia & Pattanayak (2020) examined long memory in the volatility of intraday bitcoin returns by implementing the MFDFA technique. Further, they used quantile-to-quantile regression to examine the effect of trading volume on the magnitude of extended memory. They conclude that there is long memory throughout the study period, consistent with the AMH principles. While Khursheed et al. (2020) examined the time-varying market efficiency of four digital currencies —Bitcoin, Monero, Litecoin, and Stellar. Generalised Spectral, Dominguez Lobato and the automatic portmanteau test were employed. Price movement indicated linear and nonlinear dependence, which varies over time. Meng & Li (2021) used high-frequency data of the NASDAQ order book to study informational market efficiency. Their findings supported AMH, as the level of efficiency varied over time; the period of high efficiency was followed by a period of low efficiency. Cruz-Hernández & Mora-Valencia (2024) examined the adaptive market hypothesis for Latin American stock indices by applying three versions of the variance ratio test, Dominguez Lobato, Generalised Spectral test and GARCH-M model to assess the risk-return relationship over time. The results suggested that predictability varies over time, satisfying the Adaptive Market Hypothesis. Burhan & Acar (2021) studied AMH for the Turkish Borsa Istanbul stock exchange BIST100 Index. Applied the automatic portmanteau and generalised spectral test on the daily closing price. Further, the tests were used for the Hidden Markov Model (HMM). The result validates AMH. Application of HMM confirms periodic predictability. A study by Kılıç (2020) refuted the claim of AMH for the return predictability of the Borsa Istanbul 100 index (XU100) using the Automatic Portmanteau Box-Pierce Test, Generalised Spectral Test and Wild bootstrapped Automatic Variance Ratio Test. The test results indicated that the stock market index's efficiency does not change over time, refuting AMH. AMH for decentralised finance tokens such as Chainlink, Tezos, Maker, Kyber, Network, and 0x was studied by Zhang et al. (2023). Predictability and a short period of inefficiency were reported in the prices of DeFi tokens. Akhter & Yong (2019a) examined the time-varying behaviour of the momentum and contrarian anomalies at the Dhaka Stock Exchange. AMH through calendar anomalies for the Islamic stock exchange was evaluated by Al-Khazali & Mirzaei (2017). Three well-known calendar anomalies — daily, weekly, and monthly — were evaluated using the SD test. The result indicated time-varying behaviour of calendar anomalies.

While (Xiong et al., 2019) studied AMH with anomalies for China, (Al-Khazali & Mirzaei, 2017) (Mirzaee Ghazani & Khalili Araghi, 2014) anomalies and efficiency for Iran, (Akhter & Yong, 2019b) AMH and momentum effect for Bangladesh, (Urquhart & McGroarty, 2014) calendar effect, market condition and AMH for DJIA United States,(Kim et al., 2011a) Return predictability and AMH on DJIA for United States, (Yousuf & Makina, 2022) AMH on Johannesburg for South Africa, (Kołatka, 2020a) AMH for Poland, (Ito & Sugiyama, 2009) time varying inefficiency for Japan, (Kyei et al., 2023) commodity prices, financial soundness and AMH on Gahna. Few studies have studied AMH in an Indian context. Hiremath & Kumari (2014) examined the period from the 1990s to 2013 to determine whether the adaptive hypothesis better describes the behaviour of emerging markets, using linear and nonlinear models. Linear results reported that the market moves from a period of efficiency to inefficiency, and the non-linear test indicated the possible predictability of excess return. Bhuyan et al. (2020) attempted to study evolving return predictability of the Indian stock market, BSE and NSE. Automatic portmanteau ratio and wild bootstrap automatic variance ratio were used within a rolling-window framework. The result revealed that both stock markets are informationally inefficient. The degree of predictability of the Indian stock market evolves over the period, influenced by various global events. The time-varying nexus between volatility, co-movement between stock liquidity and information efficiency for Indian, European and North-South American was studied by Patra & Hiremath (2024). Strong co-movement between market inefficiency and illiquidity arises from price impact dynamics. The time-varying relationship intensifies, suggesting that financial crisis amplifies the volatility linkage between inefficiency and illiquidity. The Indian market was found to show relatively weak dynamic conditional correlation. Patra & Hiremath (2022b)measured the market efficiency of Asia (including India), Europe, Africa, North and South America, and the Pacific Ocean region and ranked them according to the level of information efficiency. The entropy approach was deployed. The result reveals evolving efficiency that varies by region and market development stage. Emerging markets like India have improved efficiency through financial liberalisation policies but were adversely affected by global shocks. A recent study by Okorie & Lin (2021) reported information inefficiency in the Indian stock market following the coronavirus outbreak. Conditional heteroscedasticity and the martingale difference test were used to check for the adaptive market form of efficiency.

1.5.2 Political Risk (Elections) and the Stock Market

Democracies around the world are mainly classified into two types based on the style of election and power distribution: the Parliamentary System and the Presidential System. India follows a parliamentary system of democracy, in which citizens directly elect members of parliament every five years, unless the government loses the confidence of the legislature. One of the key features of a democratic setup is the election, held every five years to elect representatives to a state assembly or a national parliament. The risk associated with such elections is known as political risk.

There is no single definition of political risk. However, it is understood as the risk of unanticipated transformation in the business environment as a result of political changes, such as changes in taxation law and government policies, foreign and domestic conflicts, in addition to the quality of government institutions (Lehkonen & Heimonen, 2015)(Dimic et al., 2015; Hoi et al., 2025). These risks may also arise due to political instability, resulting in price clustering, providing an exploitable opportunity to traders (Narayan & Smyth, 2013). A study by Dimic et al. (2015) reported government actions as one of the common political risks that negatively affect stock returns across emerging, frontier, and developed markets. It also reported that emerging markets are more exposed to political risk than developed markets.

Elections, such as presidential or mayoral, have a greater influence on retail investors and their choices (Hoi et al., 2025), as they can alter government policies. Stock market participation also increases as the political orientation of voters (Kaustia & Torstila, 2011). Beyond participation, political orientation also extends to stock-specific selection tied to political ideologies (Hoi et al., 2025). Voters aligned with a particular political ideology are more optimistic about stock returns when the government is led by a particular party aligned with their views and is going into elections (Bonaparte et al., 2012). When explaining stock returns, political risk is one of the essential factors; however, it is often found to violate the classic risk-return relationship, which says that a decrease in political risk is associated with higher stock returns (Dimic et al., 2015). A study by Kim et al. (2011b) found that stock returns are highly predictable during periods of economic or political uncertainty for the Dow Jones Industrial Average Index.

1.5.3 Subsamples

Stock markets face various periodic and non-periodic events over time, including non-periodic events that can result in distinct structural breaks. The analysis, which is based solely on the full sample, is meaningless. Traditionally, various researchers had used subsamples to avoid such events (Noda, 2016). There are mainly two issues with subsamples, as listed by Noda (2016),first, identifying the cut-off point that separates the subsamples, and secondly, the width of the subsample.

Empirically, many authors divide the entire sample into subsamples based on events to study AMH. Al-Khazali & Mirzaei (2017) defined subsamples based on regional-specific events (the Asian Financial Crisis, the Period before the world financial crisis, during the financial crisis, and after the world financial crisis) to capture the effect on stock prices. Okorie & Lin (2021) considered Covid-19 ex-ante and ex-post subsamples to study the level of market information efficiency. Roy & Santhakumar (2014) considered the global financial crisis of 2007-2010 to study the persistence of time-varying market inefficiency. Numerous researchers also divided the entire sample into sub-samples to study the evolving nature of markets. Hiremath & Kumari (2014a) divided the sample into two yearly sub-samples to capture the evolving nature of the Indian stock market. In contrast, Ghazani & Khalili Araghi (2014) divided the sample every year to study the evolution of market efficiency. Akhter & Yong (2019a) divided the whole sample into a four-year subsample to study the time-varying behaviour of momentum and contrarian profits.

1.5.4 Time-varying Return Predictability and its consistency with the AMH of the Indian Stock Market

Bannigidadmath & Narayan (2016) examined time-varying predictability and mean-variance profits for the Indian market and various market sectors using financial ratios. The result showed that not all financial ratios predict returns. Evidence favoured predictability at the sector level over the market level, and the mean-variance investor could achieve statistically significant profits from all financial ratio-based predictive regression models estimated using the feasible generalised least squares estimator. Devpura et al. (2018) examined the time-varying predictability of the US stock market using monthly data from

1927 to 2014, employing an expanding-window approach estimated with a flexible generalised least squares estimator. Concluded with two key findings: first, 7 out of 14 predictors show strong evidence of time-varying predictability. For the remaining predictors, there is no predictability, or predictability is not time-dependent. Secondly, the phases of time-varying predictability help explain time variation in predictability. Charles et al. (2017) evaluated the predictive ability of financial ratios, technical indicators and short-term interest rates for stock returns of international markets, including the Indian market. By adopting the improved augmented regression method of Kim (2014a), they reported that financial ratios have weak predictive ability for stock returns. Whereas a momentum indicator (price pressure) and the short-term interest rate showed substantially greater predictive ability. Westerlund & Narayan (2015) conducted an extensive analysis of stock return predictability using a large panel of Chinese stock return data. The result indicates that when firm heterogeneity is taken into account, predictors can predict returns. They used panel predictability tests of Hjalmarsson (2010), and Westerlund and Narayan (2014). (Ito & Sugiyama, 2009) Predictability is not considered inefficiency unless it can overcome transaction costs. Meng & Li (2021) examined the predictability of returns using high-frequency (one-minute data) for market efficiency. The result showed that the market is neither efficient nor inefficient. Khursheed et al. (2020) studied the return predictability of four digital currencies for a period ranging from 2014 to 2018 by applying Dominguez Lobato and Generalised Spectral test and automatic portmanteau test. The result confirms that prices are dependent on market conditions and efficiency adheres to the Adaptive Market Hypothesis. The predictability of the Latin stock market was analysed by Cruz-Hernández & Mora-Valencia (2024) using three versions of the variance ratio test, the Dominguez Lobato test, the Generalised Spectral test, and the GARCH-M model to assess the risk-return relationship over time. The results suggested that predictability varies over time, switching between periods of efficiency and inefficiency. For Turkey, Burhan & Acar (2021) studied the predictability of the Borsa Istanbul Stock Exchange returns by applying a hidden Markov Model (HMM) to the test results of the automatic portmanteau and generalised spectral tests. The HMM test results confirm the periodic predictability. Time-varying return predictability for decentralised token was studied by Zhang et al. (2023). Findings suggested that the efficiency varies over time. The majority of tokens exhibit a short-lived period of price predictability. Verheyden et al. (2015) reported that at the beginning of the 1980s, return predictability was higher worldwide. Time-varying behaviour of momentum and contrarian profits was studied by Akhter & Yong (2019a). The result showed the existence of momentum profits for medium- and long-term reversal effects, which change over time. Ito Noda 2014 studied time-varying structure in linkages and market efficiency of the International Stock market. The result indicates that the degree of market efficiency is time-varying. Time-varying return predictability for century-long US data of the Dow Jones Industrial Average Index was studied by Kim et al. (2011b). Automatic variance ratio, automatic portmanteau test, along with the generalised spectral test, were implemented on a rolling subsample window. Economic and political crises lead to a high degree of return predictability. Predictability of returns fluctuates over time due to changing market conditions. Factors such as inflation, risk-free rates and stock market volatility had influence on predictability.

Few previous studies have examined AMH in relation to time-varying return predictability of the Indian stock market. Hiremath & Kumari (2014) address the question of whether the adaptive market hypothesis provides a better description of the behaviour of the emerging stock market, like India. Employed linear tests like the autocorrelation test, run test, variance ratio test, multiple variance ratio tests and nonlinear methods like the McLeod LI test, Tsay test, Arch-LM test, Hinich bicorrelation test, and BPS test. The linear test results indicated a cyclical pattern in autocorrelations, suggesting that the Indian stock market switched between periods of efficiency and inefficiency. The findings suggest that the Indian stock market is still evolving and not fully Adaptive. The results provide additional insights on the association between financial crises, foreign portfolio Investments and inefficiency. Hiremath & Narayan (2016) examine the adaptive market hypothesis using the Generalised Hurst exponent, derived using fixed and rolling windows. They found that the Indian stock market is moving towards efficiency as per AMH. They also ascertain a positive and significant link between the Indian market's efficiency gap and financial crises, other international shocks and major domestic policy and crisis-related events.

1.5.5 Information Efficiency of the Indian Stock Market

In an information-efficient market, picking winners and devising a portfolio strategy would be a waste of time, as there would be no undervaluation or overvaluation of securities. Information efficiency is key in devising a strategy and profiting from the market. Several studies have studied the information efficiency of the Indian Stock Market under the Efficient Market Hypothesis. Rehman et al. (2018) investigated market efficiency in Pakistan, India, and Bangladesh from 2005 to 2017. The results showed predictable stock returns, implying inefficiencies. Post the Global Financial Crisis (Jain et al., 2013), the study examined information efficiency in the weak form of the Indian stock market over the entire period of the global financial crisis, indicating that the market was weakly efficient. Mehmet (2008) studied market efficiency using extensive data to evaluate the Indian stock market for possible diversification by international investors. The results showed strong integration between the Indian and international markets, indicating minimal diversification benefits. Further predictability was possible, indicating market inefficiencies. Pandey (2003) studied the efficiency of the Indian stock market. The evidence indicated that the market was Inefficient.

Globally, various studies have studied stock market efficiency under the Efficient Market Hypothesis. Griffin 2006 examined the speed at which public and private information is incorporated into prices. Emerging markets showed remarkable efficiency in incorporating market-wide information. Gardini et al. (2025) examined the extent to which stock markets are informationally efficient. The result showed the existence of market behaviour similar to the Adaptive Market Hypothesis. Pesaran (2010) Focuses on the theoretical foundation of EMH and shows that market efficiency could coexist with heterogeneous beliefs and individual irrationality, as individual errors are cross-sectionally weakly dependent. However, during periods of excessive optimism or pessimism in the market, individual judgment errors tend to become highly correlated across investors, leading to collective behaviour that can cause significant departures from market efficiency.

Several authors have studied information efficiency under AMH globally across various markets. Kyei et al. (2023) examined how well the effect of commodity prices is reflected in banking sectors' financial soundness indicators under various market conditions in Ghana, using quantile regression and quantile-based causality estimation. The result indicated inefficiency in the soundness of the financial sector. Khuntia & Pattanayak (2018) studied the evolving efficiency in bitcoin prices and concluded that dynamic efficiency exists, which supports the AMH proposition. The existence of behavioural biases and the creation of events can change efficiency. Further, they concluded that past studies claiming that bitcoin price movements are either efficient or inefficient under the EMH framework are incorrect. They deployed the DL and GS tests for rolling windows to evaluate the same. Varghese & Madhavan (2022) tested homogeneity in the degree of efficiency of the crude oil benchmarks, namely West Texas Intermediate, Brent, and Dubai crude prices, using a battery of nonparametric tests. The result showed that efficiency is not homogeneous across the market. Compared with the WTI market, the Brent and Dubai markets were found to be more inefficient. Noda (2016) examined the degree of market efficiency of the Japanese stock market TOPIX and TSE2 under AMH. They employed a time-varying model of Ito et al. (2014). The result indicated a change in efficiency in both markets. Further, TOPIX was more efficient than TSE2. The results in both the market supported AMH. Meng & Li (2021) analysed the information efficiency of high-frequency data of the S&P exchange-traded fund (SPY). They concluded that efficiency varies over time. Periods of high efficiency are followed by periods of low efficiency. They actively process information during the lower-efficiency period by adding and cancelling limit orders. Kılıç (2020) studied the degree of efficiency of the Borsa Istanbul stock market index XUV100. The result indicates that the efficiency of the stock market index remains unchanged over time, regardless of market conditions. Whether the financial market is perfectly efficient is another question that Verheyden et al. (2015) studied. They reported efficiency between both extreme ends of the spectrum.

The literature on the information efficiency of the Indian Stock market from an Adaptive Market Hypothesis perspective is limited, given its status as one of the fastest-developing markets. Few studies, such as those by Patra & Hiremath (2024), have examined the influence of economic and non-economic factors on stock market efficiency to assess the time-varying nexus between information efficiency and various aspects of liquidity — namely, tightness, depth, breadth, immediacy, and adjusted immediacy—in the Indian stock market. A dynamic relationship between inefficiency and illiquidity, driven by price impact, was observed. Recent post-COVID-19 studies on the Indian market indicated that India is more information-inefficient in the long run (Okorie & Lin, 2021). They employed a rolling-window approach on the full sample and on the ex-ante and ex-post subsamples, using martingale difference spectral and conditional heteroskedasticity test statistics.

1.5.6 Time-Varying Inefficiency of the Indian Stock Market

Time-varying means something that changes over time, whereas Inefficiency means the existence of an exploitable opportunity: i.e., past stock information can be used to predict future stock prices. Imperfections in price-formation processes can manifest as these Inefficiencies. In other words, it can be described as predictable price-formation processes. Inefficiencies could arise primarily during periods of significant institutional and technological change (Pesaran, 2010). While Pesaran (2010) Highlights that it is impossible to know when or where market inefficiencies arise, though they are believed to occur from time to time. Various inefficiencies have been pointed out by various studies, such as (Hiremath & Narayan, 2016; Khuntia & Pattanayak, 2018) pointed out inefficiencies due to macroeconomic events. Studies such as those by Fiedor (2015) indicated significant inefficiency at the small-scale level in the price-formation process on Warsaw's market. Zunino et al. (2008) stated that ranking of Inefficiency can provide important information for policy makers, regulators so that they can devise appropiate policies to improve market efficiency. As Lo argues, both periods of market efficiency and inefficiency are prevalent at various points in time. A significant chunk of the literature on the Adaptive Market Hypothesis is devoted to studying efficiency, while ignoring inefficiencies. Inefficiencies are studied by assuming the market is weak-form efficient under AMH.

Various studies have examined the weak-form efficiency of the Indian Stock Market under the Efficient Market Hypothesis. Jain et al. (2013) studied information efficiency in the weak-form sense of the Indian Stock Market during the period of recession. The result indicated that the Indian market is weakly efficient. In contrast, a study by Mishra et al. (2015) on weak-form efficiency found no weak-form efficiency in the Indian Stock Market for the period from 1999 to 2012. Further, Dsouza & Mallikarjunappa (2015) examined the weak-form efficiency of 200 listed companies on the BSE 200 and concluded that the Indian Stock market is not weak-form efficient. Similarly, Parthsarathy, (2016) examined the weak-form efficiency of Indian Indices. The results indicated evidence against the evolution of inefficiency in the weak form.

Globally, literature on inefficiencies under AMH is sparse. Ito and Sugiyama (2009) studied the time-varying structure of market inefficiency. The result indicated that the degree of market inefficiencies varies through time. In contrast, Bianchi & Pianese (2018) used the Hurst Holder exponent to quantify dynamically the inefficiency of a market. Some unique findings were reported first: the market alternates between efficient and inefficient periods lasting months. Secondly, positive and negative inefficiencies exhibit distinct patterns. The buildup of positive inefficiencies tends to occur more gradually than that of negative inefficiencies. Thirdly, negative inefficiencies tend to co-occur across markets, whereas positive inefficiencies appear to be more market-dependent. Fourthly, in the long run, positive and negative inefficiencies tend to balance each other out. Verheyden et al. (2015) empirically investigated AMH's weak-form efficiency across the US, Japanese, and European stock markets. The period beginning in the 1980s in global financial markets appears to exhibit a higher degree of return predictability, implying lower weak-form efficiency. Several studies demonstrate that periods of inefficiency coincide with significant developments, such as political and economic events. (Hiremath & Narayan, 2016; Khuntia & Pattanayak, 2018) pointed out inefficiencies due to macroeconomic events. Roy & Santhakumar (2014) reveal that variations in the degree of relative stock market inefficiency and the persistence of global market linkages provide rational investors and arbitrageurs with the opportunity to hold a basket of international diversified stock portfolios, with the opportunity to create an arbitrage position through the maximisation of overall returns. A recent study by Bhuyan et al. (2020) revealed that the Indian stock market BSE and NSE are informationally inefficient in the weak form. They reported that NSE was more efficient than BSE. Automatic portmanteau ratio and wild bootstrap automatic variance test were used for analysis, along with a rolling window framework. Zunino et al. (2008) used a multifractal approach to study stock market inefficiency of developed and emerging stock market indices. Multifractality can be used to measure how complex or irregular price movements are in a market. Using multifractality, an inefficiency ranking can be devised from multifractal analysis. Higher multifractality was observed for emerging markets, including India, indicating less efficiency.

1.6 Research Gap

Despite early studies on AMH, there is no literature on AMH during the phases of parliamentary elections. Even after more than two decades, the research on AMH is still in its infancy (Patra & Hiremath, 2022). The pertinent studies listed above do not study the degree of efficiency by applying the MFDFA approach. Measuring the degree allows us to understand whether the efficiency improves or deteriorates. Though the efficient market hypothesis says that returns are generated by random processes, in reality, these processes are influenced by large and small fluctuations across multiple periods. One such period can be a parliamentary election, which decides the upcoming business environment and government policies.

Further, basically, two approaches are used to study AMH. The first approach involves a time-varying model to measure market efficiency, while the second approach utilises various statistical methods, including the moving window method (Noda, 2016), to investigate market efficiency. To the best of our knowledge, both approaches are widely used to study market efficiency, excluding market inefficiencies and detecting these inefficiencies has been a crucial objective of trading practitioners (Khuntia & Pattanayak, 2020). However, as Lo argues, both period efficiency and inefficiency exist in a market. Therefore, there is a need to address this gap by examining the time variation in the degree of market inefficiency of the Indian Stock Market.

1.7 Research Questions

The following research question was framed based on the research gap identified through the literature review.

- Does the Indian Stock Market evolve or follow the pattern as mentioned by the Efficient Market Hypothesis or the Adaptive Market Hypothesis?
- Are the phases of the parliamentary election efficient or inefficient on the Indian stock market?
- Does the degree of efficiency vary across the market and through various phases of parliamentary elections?
- Can the inefficient phases of the stock market be modelled?

1.8 Objectives for the Study

1.8.1 Objective I

To study the Time-varying Return Predictability of the major Indian Stock Indices and to examine whether evolution is consistent with the AMH.

Sub Objective: -

1) To examine AMH during the phases of parliamentary elections for the Indian Stock Indices S&P BSE Sensex.
2) To capture the evolving return predictability.

1.8.2 Objective II

To analyse the Informational Efficiency of the Indian Stock Market and examine its consistency with AMH. (i.e Degree of Market Efficiency).

Sub Objective: -

1) To study the Degree of Market Efficiency in the case of BSE- Sensex over the long run and short run.
2) To apply Seasonal and Trend Decomposition using LOESS before applying MF-DFA.

1.8.3 Objective III

To study the Time-varying Inefficiency of the Indian Stock Market.

Sub Objective: -

1) To examine the Time-varying Inefficiency of the Indian Stock Market.

1.9 Research Methodology

The methodology used for various objectives has been presented here, objective-wise, as follows.

1.9.1 Research Methodology for Objective I

1.9.1.1 Period of the study

For the study, the data have been collected for the Indian Stock Market Index BSE Sensex for the period from 1989 to 2024. The data have been divided into two parts: the full sample and the subsample.

Table 1: Definition of Subsamples and Study Period.

Period	Date	Elections
BSE Sensex (Full Sample)	January 1st 1989 to 31st Dec 2024	-
Subsample I	April 1 to July 31 1991	10th Parliamentary Election
Subsample II	March 1 to June 30 1996	11th Parliamentary Election
Subsample III	January 1 to April 31 1998	12th Parliamentary Election
Subsample IV	August 1 to November 31 1999	13th Parliamentary Election
Subsample V	March 1 to June 30 2004	14th Parliamentary Election
Subsample VI	March 1 to June 30 2009	15th Parliamentary Election
Subsample VII	March 1 to June 31 2014	16th Parliamentary Election
Subsample VIII	March 1 to June 1 2019	17th Parliamentary Election
Subsample IX	March 1 to June 30 2024	18th Parliamentary Election

Source: - Author Compilation.

1.9.1.2 Sample Design

For the study, the Bombay Stock Exchange Sensex index, which comprises 30 large, well-established, and financially sound companies, has been selected. It will represent as a proxy of the Indian Stock Market for the entire period of study.

1.9.1.3 Data Variables and Sources

The dataset includes daily closing Index prices in Excel CSV format. Collected from the official website of the Bombay Stock Exchange (https://www.bseindia.com/). The daily

Index prices of the BSE Sensex indices were converted to the daily logarithmic returns using the following formula:

$$R_t = Ln\left(\frac{p_t}{p_{t-1}}\right) * 100$$

1.9.1.4 Statistical and Econometric Techniques

To assess the time-varying predictability of the Indian stock market index, the BSE Sensex, during the period of various parliamentary elections. We use a non-overlapping rolling window of 100 days for the full sample and 10 days for the subsample. We employ Generalised spectral (GS) tests, along with the Dominguez-Lobato (DL) test, which are used to test the martingale difference hypothesis and to capture evolving linear and nonlinear dependence in returns. To gain a better understanding of the evolution of efficiency, we employ both a parametric-based variance ratio test and a non-parametric-based variance ratio test.

1.9.1.4.1 Variance Ratio Test

Lo and Mackinlay (1988) proposed the variance ratio test. It is based on the property that the variance of subsequent returns is a random walk; X_t is linear in its data interval. This means that the variance and mean of r_t -r_{t-1} are required to be twice the variance of r_t. Therefore, the RWH can be checked by comparing two-period returns, $r_t(2)= r_t - r_{t-1},$ to twice the variance of a one-period return r_t. Then the variance ratio test is given as VR (2) is

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

$$= \frac{..2Var[r_t] + 2\,Cov[r_t, r_{t-1}]}{2Var[r_t]}$$

$$VR(2) = 1 + p(1) \qquad (1)$$

where p (1) is the first-order autocorrelation coefficient of returns [r_t]. RWH requires that autocorrelation holds true when VR(2) =1. The standard normal test statistic under the assumption of homoscedasticity and a random walk, the variance ratio is expected to be equal to unity. It is given as

$$Z(q) = \frac{(VR(q)-1)}{\sqrt{\emptyset(q)}} \sim N(0,1) \qquad (2a)$$

Where,

$$\emptyset(q) = \frac{2(2q-1)(q-1)}{3q(nq)} \tag{2b}$$

Lo-Mackinlay standard normal test for heteroscedasticity, which is given as

$$Z*(q) = \frac{VR(q)-1}{\varphi*(q)^{\frac{1}{2}}} \tag{2c}$$

The returns are considered a random walk when the variance ratio at a holding period q is unity. Here, the variance ratio of less than one implies negative autocorrelation and greater than one indicates positive autocorrelation.

1.9.1.4.2 Multiple Variance Ratio Tests

To overcome the drawback of size distortion resulting from the sequential procedure and the joint nature of the random walk, Chow and Denning (1993) proposed multiple variance ratio tests. Variance ratio estimates {$VR_{(qi)}$i| =1,2,3,……, L}, corresponding to a set of pre-defined numbers of lags [q_i| I =1,2,3,….., L]. Multiple and alternative hypotheses are as follows

$$H_{oi} = VR = 0\ for\ i = 1,2,\ldots.,m \tag{3a}$$

$$H_{1i} = VR(q_i) \neq\ 0 \text{ for any I } = 1,2,\ldots.,\text{m} \tag{3b}$$

The rejection of H_{0I} will lead to the rejection of the Random Walk Hypothesis. Chow-Denning test statistic is given:

$$CD = \sqrt{T}\ \max_{1\leq i\leq}|Z^*(qi)| \tag{3c}$$

Chow-Denning test statistic follows the studentized maximum modulus, SMM (*α, m, T*), distribution with *m* parameter and *T* degrees of freedom. The decision about whether to reject the null hypothesis can be based on the maximum absolute value of the individual variance ratio test statistics. If the standardised Chow-Denning test statistic is greater than the SMM critical values at the chosen significance level, then RWH is rejected.

1.9.1.4.3 Non-Parametric Variance Ratio Test

The non-parametric variance ratio (VR) test, introduced by Wright (2000), is an alternative to the traditional parametric Lo–Mackinlay VR test. While the parametric test assumes normality and homoskedasticity of returns, the nonparametric version relaxes these assumptions and is therefore more robust to financial time series, which often exhibit fat tails, heteroscedasticity, and nonnormal distributions**.** The test is based on rank and sign transformations of the return series rather than the raw returns. Because it does not depend on distributional assumptions, it provides more reliable inference when data exhibit volatility clustering or outliers.

The nonparametric VR test examines whether the variance of k-period returns equals k times the variance of 1-period returns. If this holds, the series follows a random walk, implying market efficiency. Significant deviations from this relationship indicate return predictability and, by extension, market inefficiency. It is useful when return series are not well-behaved, as a parametric test may give misleading results.

1.9.1.4.4 Rank-based Variance Ratio Test

Four alternative tests have been given (Wright, 2000) based on ranks and sign to the parametric variance ratio test. Let $r(x_t)$ be the rank of x_t among $x_1, x_2, x_3, \ldots\ldots, x_t$ and the corresponding standardised (zero-mean, unit variance) series r_{it} given by:

$$r_{it} = (r(x_t) - \tfrac{T+1}{2}) / \sqrt{\tfrac{(T-1)(T+1)}{12}} \tag{4a}$$

Simply substitutes r_{it} to x_t in the definition of the test statistic Z_T so that the proposed rank-based test statistic is:

$$R_1(k) = \left(\frac{\sum_{k+1}^{T}(r_{1t}+r_{1t-1}+\cdots+r_{it-k+1})^2}{k\,\sum_1^T r_{1t}^2}\right) X \;\left(\frac{2(2K-1)(K-1)}{3kT}\right)^{-\frac{1}{2}} \tag{4b}$$

$$R *_1(k) = \left(\frac{\sum_{k+1}^{T}\left(r_{1t}^{*}+r_{1t-1}^{*}+\cdots+r_{1t-k+1}^{*}\right)^2}{k\,\sum_1^T r_{1t}^{*2}}\right) X \;\left(\frac{2(2K-1)(K-1)}{3kT}\right)^{-\frac{1}{2}} \tag{4c}$$

1.9.1.4.5 Sign-based Variance Ratio Test

Sign-based variance ratio test statistic S_1 is defined as

$$s_1 = \left(\frac{\frac{1}{Tk}\sum_{t=k}^{T}(s_1+s_{t-1}\ldots+s_{t-1k+1})^2}{\frac{1}{T}\sum_{t=1}^{T}s_t^2} - 1\right) x \;\left(\frac{2(2k-1)(k-1)}{3kT}\right)^{-1/2} \tag{5a}$$

1.9.1.4.6 Generalised Spectral Test

The generalised Spectral Test (GS) of the Martingale Difference Hypothesis is used to determine whether a financial time series follows a martingale-difference sequence, indicating market efficiency. A time series X_t is a martingale difference sequence if the conditional expectation of the next value, given all past information, is zero. Mathematically, it's defined as:

$$E[X_{T+1}|f_t] + 0$$

where f_t is the information available up to time *t.*

Generalised Spectral Test uses a spectral distribution function to analyse the time series, which helps to detect dependencies in the data.

The spectral Distribution Function is defined as:

$$\mathrm{H}(\lambda)=\lambda;\ \psi(\delta_o(\lambda)) + 2\sum_{j=1}^{\infty} \delta_j\ (\lambda)\frac{sin(j\pi\lambda)}{j\pi}$$

Here, λ is a real number between 0 and 1, and $\delta_j(\lambda)$ represents the coefficient capturing dependencies at different lags. The test statistic measures the distance between the estimated spectral distribution $\widehat{H}$ and the expected distribution under the null hypothesis H_0. It is defined as:

$$\mathrm{s_T}(;)\ = \begin{pmatrix}\lambda;\psi\\0.5T\end{pmatrix}^{1/2}\ (\widehat{H}(\lambda;\psi)\ -\ H_0(\lambda;\psi))$$

Cramer-von Mises Norm is used to compute D_n^2, which measures the overall deviation of the time series from the behaviour expected under the null hypothesis. It is defined as:

$$D_n^2 = \sum_{j=1}^{n}\frac{1}{n}\ (\frac{j}{j\pi})^2\ \sum_{t=j+1}^{n}\sum_{s=j+1}^{n}(yt - y_{n,j} - y_s + y_{n,j}exp[i(y_{t,j} - y_{s,j})])^2$$

If the value of D_n^2 is significantly high (exceeds a critical value), the null hypothesis of the martingale difference sequence is rejected. This suggests the presence of predictable patterns or dependencies in the time series.

1.9.1.4.7 Dominguez -Lobato Test

It is a non-parametric statistical method used to test the Martingale Difference Hypothesis (MDH) in time-series data to assess the unpredictability of asset returns. A time series $\{Y_t\}$

is a martingale difference sequence if $E[Y_{t+1}|F_t] = 0$ for all t, where F_t is the information set available at a given time t. That implies that, given the past information, the best prediction of the next value is zero, reflecting the idea of unpredictability in efficient markets. The Dominguez-Lobato test statistic is based on the autocorrelations of the squared observations. First, we calculate the squared observations Y_t^2, then the sample autocorrelations of Y_t^2 for different lags k., the sample ACF at lag k is given by:

$$\hat{p}(k) = \frac{\sum_{t=k+1}^{T}(Y_t^2 - \bar{Y}^2)(Y_{t-1}^2 - \bar{Y}^2)}{\sum_{t=1}^{T}(Y_t^2 - \bar{Y}^2)^2}$$

Where $\bar{Y}^2$ is the sample mean of Y_t^2, and T is the sample size. The test statistic is a function of the sample ACFs. It is typically a sum of squared autocorrelations up to a certain lag M:

$$D_T = T\sum_{K=1}^{M}\hat{P}(K)^2$$

1.9.2 Research Methodology for Objective II

1.9.2.1 Period of the Study

For the study, data have been collected for the Indian Stock Market Index, the BSE Sensex for the period from 1989 to 2024, and the NSE Nifty from 1990 to 2024. The data has been divided into two parts: the full sample and the subsample for the BSE Sensex.

Table 2: Definition of Subsamples and Study Period.

Period	Date	Elections
NSE Nifty (Full Sample)	July 3rd 1990 to 31st Dec 2024	-
BSE Sensex (Full Sample)	January 1st 1989 to 31st Dec 2024	-
Subsample I	April 1 to July 31 1991	10th Parliamentary Election
Subsample II	March 1 to June 30 1996	11th Parliamentary Election
Subsample III	January 1 to April 31 1998	12th Parliamentary Election
Subsample IV	August 1 to November 31 1999	13th Parliamentary Election
Subsample V	March 1 to June 30 2004	14th Parliamentary Election
Subsample VI	March 1 to June 30 2009	15th Parliamentary Election
Subsample VII	March 1 to June 31 2014	16th Parliamentary Election
Subsample VIII	March 1 to June 1 2019	17th Parliamentary Election
Subsample IX	March 1 to June 30 2024	18th Parliamentary Election

Source: - Authors Compilation.

1.9.2.2 Sample Design

For the study, the Bombay Stock Exchange Sensex index, which comprises 30 large, well-established, and financially sound companies, has been selected. It will serve as a proxy for the Indian stock market throughout the study period.

1.9.2.3 Data Variables and Sources

The dataset includes daily closing Index prices in Excel CSV format. Collected from the official website of the Bombay Stock Exchange (https://www.bseindia.com/). The daily stock prices of the BSE Sensex indices were converted to the daily logarithmic returns using the following formula:

$$R_t = Ln\left(\frac{p_t}{p_{t-1}}\right) * 100$$

1.9.2.4 Statistical and Econometric Techniques

1.9.2.4.1 Seasonal and Trend Decomposition using LOESS (STL)

We start by breaking down the Index returns data into two main components: deterministic and stochastic. Deterministic components are those we can predict, such as trends and seasonal patterns. Stochastic components are more random and unpredictable. To isolate the stochastic part, we use the seasonal and trend decomposition using the LOESS (STL) method. This method separates the data into three parts: trend (long-term behaviour), seasonal (repeating patterns) and remainder (random fluctuations). STL works in three steps: initialising the trend, refining the trend and seasonal components while reducing the influence of outliers, and then extracting the residual. STL is preferred over other methods because it can handle various types of seasonality, not just monthly or quarterly patterns. It allows the seasonal component to change over time, giving us more flexibility. We can adjust parameters to control how quickly the seasonal component changes and how smooth the trend is, plus, STL is robust against outliers. In our study, we use the R statistical package and its STL function to perform STL decomposition. We set specific parameters for the function tailored to our data, such as the window size for seasonal extraction and the number of iterations to refine the decomposition. We can separate the predictable patterns (like trends and seasonality) and focus on the more random, unpredictable fluctuations. This allows us to better understand the underlying dynamics of the stock market and analyse long-term correlations using techniques such as Multifractal Detrended Fluctuation Analysis (MF-DFA).

1.9.2.4.2 Multifractal Detrended Fluctuation Analysis (MF-DFA)

The Multifractal Detrended Fluctuation Analysis (MF-DFA) is a powerful technique used for detecting multifractality in time series data. It is beneficial for identifying long-term correlations in non-stationary time series, such as stock market returns. The steps involved are.

Step 1: Construction of profile (Y(j)):

Subtract the average value of the time series from each data point to obtain the remainder component. Integrate the remainder component to construct the profile:

$$\text{Y(J)} = \sum_{i=1}^{j}(R(i) \ - \ R)$$

Step 2: Division into segments

Divide the profile Y(J) into $N_s \ = int(N/S)$ non-overlapping segments of equal length s. If N is not an integer multiple of *S*, disregard the short part of the profile at the end and start the subdivision from the opposite end, resulting in a total of $2N_s$ segments.

Step 3: Local Trend Calculation

Fit a polynomial of degree m to each segment using the least squares method to approximate the profile within each segment. Calculate the variance using the formula:

$$\text{For segments } \nu \ = 1,2, \dots, N_s\text{: } F_2\ (\mathcal{S}, \nu) = [(\nu - 1)s + j] - y_\nu(j)]$$

$$\text{For segments } \nu = N_s \ + \ 2, \dots, 2N_s : F_2\ (\mathcal{S}, \nu) = \frac{1}{s}\sum_{j=1}^{s}[Y[(\nu - N_s)s + j] - y_\nu(j)]$$

Where $y\nu(j)$ is the polynomial fit in segment *v*.

Step 4: Calculation of fluctuation function

Compute the *qth-order* fluctuation functions using the formula:

$$\text{For } q \neq 0\text{: } F_q(s) \ = [\frac{1}{2N_s}\sum_{V=1}^{2N_S}[F_2(S,V)]^{q/2}]^{1/q}$$

$$\text{For } q \neq 0\text{: } F_0(s) \ = \left[\frac{1}{4N_s}\sum_{V=1}^{2N_S} IN[F_2(S,V)]\right]$$

Step 5: Determination of Scaling exponent

If F_q (s) follows a power law, plot it in a log-log scale to obtain the relationship F_q(s) $\propto s^{h_q}$. the exponent h_q is called generalized hurst exponent. For stationary series, h_2 becomes the Hurst exponent. Use h_q to measure market efficiency: 0.5 < $h_q < 1$ implies positive autocorrelation, $h_q \approx$ 1 indicates large and abrupt changes, and 0 < h_q < implies negative autocorrelation.

Step 6: Analysis of multifractality.

Check if h_q depends on q and monotonically decreases as q increases to determine multifractality. Calculate the Rényi exponent $\tau(q) = qh_q - 1$.

Analyse the multifractal spectrum $f(\alpha) = q\alpha - \tau(q), where\ \alpha$= h_q+q$\frac{dh_q}{dh}$ - τ (q).

The degree of multifractality is measured using the range of generalised Hurst exponents: D_h = max(h_q) - min(h_q), where a higher D_h Indicates a more multifractal series.

1.9.3 Research Methodology for Objective III

1.9.3.1 Period of the Study

For the study, data were collected for the Indian Stock Market Index, BSE Sensex, for the period from 1989 to 2024. The data have been divided into two parts: the full sample and the subsample, as there is a Possibility of various non-periodic events resulting in distinct structural breaks. The analysis, which is based solely on the entire sample, is meaningless. So, we introduce overlapping sub-samples.

Table 3: Definition of Subsamples and Study Period

Period	Date	Elections
BSE Sensex (Full Sample)	January 1st 1989 to 31st Dec 2024	-
Subsample I	April 1 to July 31 1991	10th Parliamentary Election
Subsample II	March 1 to June 30 1996	11th Parliamentary Election
Subsample III	January 1 to April 31 1998	12th Parliamentary Election
Subsample IV	August 1 to November 31 1999	13th Parliamentary Election
Subsample V	March 1 to June 30 2004	14th Parliamentary Election
Subsample VI	March 1 to June 30 2009	15th Parliamentary Election
Subsample VII	March 1 to June 31 2014	16th Parliamentary Election
Subsample VIII	March 1 to June 1 2019	17th Parliamentary Election
Subsample IX	March 1 to June 30 2024	18th Parliamentary Election

Source: - Authors Compilation

1.9.3.2 Sample Design

For the study, the Bombay Stock Exchange Sensex index, which comprises 30 large, well-established, and financially sound companies, has been selected. It will represent as a proxy of the Indian Stock Market for the entire period of study.

1.9.3.3 Data Variables and Sources

The dataset includes daily closing Index prices in Excel CSV format. Collected from the official website of the Bombay Stock Exchange (https://www.bseindia.com/). The daily Index prices of the BSE Sensex indices were converted to the daily logarithmic returns using the following formula:

$$R_t = Ln\left(\frac{p_t}{p_{t-1}}\right) * 100$$

1.9.3.4 Statistical and Econometric Techniques

We apply the moving-window method with a width of 100 to the full sample and 10 to the subsample, using returns, and calculate the first-order correlation for both the full sample and the subsample to examine the time-varying structure of the market. The Augmented Dickey-Fuller (ADF) test is employed to detect the presence of a unit root, utilising an appropriate lag selection criterion.

To gain a better understanding, we employ the methodology used by Ito & Sugiyama (2009), which involves a state-space model with time-varying AR Coefficients. Here, the state space model consists of an observation equation with a time-varying AR Coefficient and a transition equation that describes how the coefficient evolves. We set the initial values for both the state variable and the returns data to zero. A state variable being zero indicates that the market is perfectly efficient. We verify the robustness of the estimation result by changing the initial values of the state variables. To estimate the changing coefficient, we apply the Kalman smoother, which helps uncover the hidden trajectory of market inefficiency.

The Observation Equation is expressed as

$$x_t = (x_{t-1,}\ \ x_{t-2} \cdots \ \ x_{t-k}) \begin{pmatrix} \alpha_{1,t} \\ \alpha_{2,t} \\ \vdots \\ \alpha_{k,t} \end{pmatrix} + u_t, u_t\ N(0, \sigma_U^2)\ \ldots\ldots\ldots (1)$$

$$x_t : Observed\ Index\ return\ at\ time\ t$$

$$\alpha_{i,t} : Time\ Varying\ AR\ Coeficient$$

$$u_t: Observation\ noise\ (assumed\ Gaussian\ with\ mean\ 0,\ variance\ \sigma_u^2)$$

and a transition equation, formed based on the autocorrelation series.

$$\begin{pmatrix} \alpha_{1,t} \\ \alpha_{2,t} \\ \ddots \\ \cdot\, \alpha_{k,t} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ . & . & . \\ . & . & . \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \alpha_{1,t-1} \\ \alpha_{2,t-1} \\ \ddots \\ \cdot\, \alpha_{k,t} - 1 \end{pmatrix} + \begin{pmatrix} v_{1,t} \\ v_{2,t} \\ \ddots \\ \cdot\, v_{k,t} \end{pmatrix},\ v_t \sim N_k(0, \sigma_U^2 I)\ \ldots\ldots.\ (2)$$

State Variable $(\alpha_{1,t})$

$v_{1,t}$ *: Process Noise*

1.10 Hypothesis of the study

To analyse the objectives of the study, we have framed the hypothesis. The hypotheses are presented as follows.

1.10.1 Hypothesis to examine the presence of a unit root in the data

H0a: The variable has a unit root

1.10.2 Hypothesis to examine the Random Walk

H0b: The return series follows a random walk

1.10.3 Hypothesis to check for Nonlinearity in a time series

H0c: The series is linearly independent and follows a martingale difference sequence.

1.10.4 Hypothesis to examine Multifractality

H0d: The index return series is monofractal and follows weak-form market efficiency.

1.10.5 Hypothesis to study the Time-varying AR(1) Coefficient estimated with a Kalman filter to measure Market Inefficiency

H0e: The time-varying AR Coefficient is always zero, and returns cannot be predicted.

1.11 Organisation of study

Chapter 1 introduces the study, outlines the need for the study, the scope of the study, the significance of the study, the literature review, the research gaps, the research questions, and the objectives of the study, and provides a detailed research methodology.

Chapter 2 includes a detailed discussion of the analysis of Objective I.

Chapter 3 includes a detailed discussion of the analysis of Objective II.

Chapter 4 includes a detailed discussion of the analysis of Objective III.

Chapter 5 reports the findings of the study, the conclusion of the study, recommendations of the study, policy implications of the study, the contribution of the study, limitations of the study and scope of further research.

Chapter 2

Time-varying Return Predictability of the BSE Sensex and its Evolution.

2.1 Introduction

This chapter examines the evolution of return predictability and market efficiency of the BSE Sensex over the full sample period and across nine election-linked subsamples. Using a combination of parametric and non-parametric techniques—including descriptive statistics, diagnostic tests, Lo–MacKinlay variance ratio tests, Wright's non-parametric tests, Chow–Denning multiple variance ratio tests, and the Generalised Spectral (GS) and Dominguez–Lobato (DL) tests—the chapter investigates whether the Sensex returns follow the Random Walk Hypothesis (RWH) and the Martingale Difference Hypothesis (MDH).

Given the unique political and economic environment surrounding Indian parliamentary elections, the subsamples provide a natural framework to assess the time-varying behaviour of market efficiency, in line with the Adaptive Market Hypothesis (AMH**)**. The empirical analysis highlights how periods of heightened uncertainty, such as elections or crisis phases, influence return dynamics, predictability, and the overall efficiency of the Indian stock market.

2.2 Historical trend of Sensex with Election Cycles and Financial Crisis.

The plot of the daily closing prices of the BSE Sensex from 1989 to 2025 shows a strong long-term upward trend, despite temporary, sharp declines during significant events such as the Asian Financial Crisis, the Dot-Com bubble, the Global Financial Crisis of 2008, and the COVID-19 crash. Election periods induce only mild, short-lived volatility without altering the broader growth trajectory, illustrating the market's resilience. The accompanying log-returns plot further reinforces this behaviour, showing apparent volatility clustering and occasional extreme spikes associated with significant economic and political shocks. Most returns remain within the overall volatility band, indicating that while extreme events are rare, they exert a significant short-term impact. Together, the plots demonstrate an adaptive pattern in the Indian stock market, consistent with the Adaptive Market Hypothesis, which posits that market efficiency varies over time in response to evolving conditions.

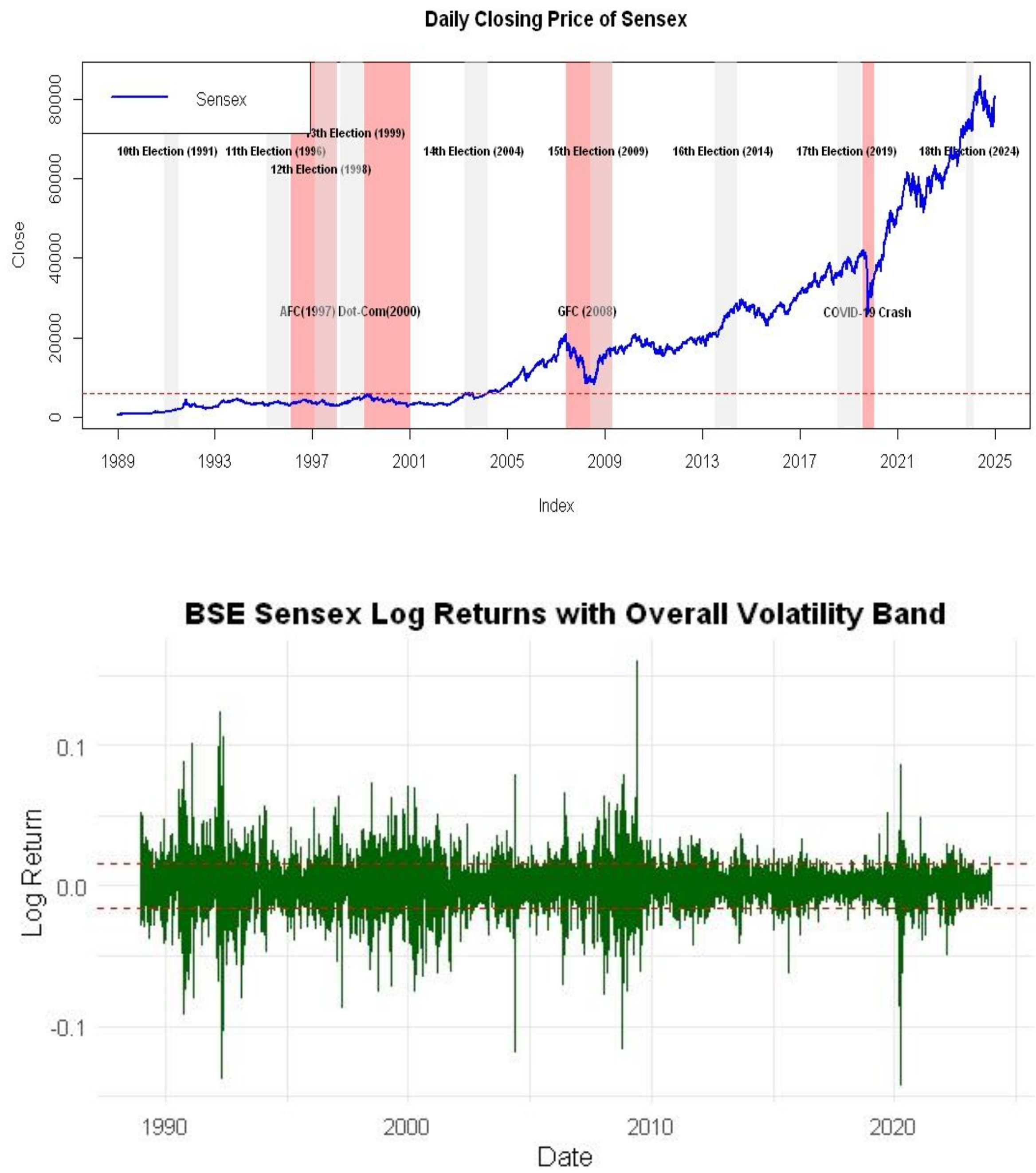


Figure 1: BSE Sensex price movement and log return Volatility across major events (1989-2025).

2.3 Empirical Results

Table 4 describes the basic statistics for the daily returns of the BSE(Sensex) Index. The mean return is positive for the full sample period and various sub-sample periods, except for the BSE subsample III and subsample V, where it is negative. The Mean return tends to be higher for BSE Sensex and for subsample VI (1^{st} March to 30^{th} June 2009). This subsample

VI preceded the 2008 financial crisis for both indices. Higher volatility was reported for Subsamples III, V, and VI. One interesting thing to note is that, in both the pre- and post-financial crisis periods, parliamentary elections were volatile, but the latter period was more volatile. Skewness is negative for the full sample, subsample-III, subsample-V and subsample IX. In contrast, it is positive for all other Subsamples, implying that the returns are flatter to the left for the full sample and subsample-III and subsample-V compared to the normal distribution.

Table 4: Descriptive Statistics for the Daily Returns of BSE (Sensex Index) with respective Subsamples.

	Obs	Mean	Median	Std. Dev.	Min	Max	Skew.	Kurt.
Sensex	8434	0.052	0.078	1.64	-0.141	15.98	-0.16	7.20
BSE I	76	0.419	0.478	1.68	-4.229	4.582	0.04	0.19
BSE II	77	0.120	0.307	1.35	-2.714	3.714	0.21	-0.26
BSE III	86	-0.270	-0.267	2.28	-7.502	7.314	-0.60	1.23
BSE IV	82	0.031	-0.153	1.60	-3.989	5.495	0.37	1.74
BSE V	84	-0.209	0.023	2.24	-11.809	7.931	-1.40	8.74
BSE VI	78	0.672	0.497	2.79	-4.898	15.989	2.03	9.59
BSE VI	86	0.243	0.090	0.82	-1.370	2.868	0.70	0.50
BSE VIII	78	0.121	0.167	0.84	-1.391	3.680	0.82	2.33
BSE IX	82	0.107	0.123	1.07	-5.911	3.334	-1.57	12.03

Notes: 1) “Obs” denotes Observation.
Source: -Authors Compilation.

Kurtosis indicates a sharp peak of the return’s distribution compared to a normal distribution. The peakiness was higher post-financial crisis for both indices. The Jarque-Bera test tests whether the return is normally distributed. A low p-value below 0.05 indicates a departure from normality. BSE sample, III, IV, V, VI, and XI, returns do not follow a normal distribution.

Table 5 describes the diagnostic test performed on the BSE Sensex Index data and its Subsample. The Augmented Dickey-Fuller (ADF) test is used to determine whether a time series is stationary. T-statistic at 1%, 5% and 10% significance has been reported. Revealing that all data subsamples are stationary. Ljung-Box test results show that, across all samples, there is no significant autocorrelation in returns, except for BSE VI and BSE IX.

Table 5: Diagnostic Test for the Daily Returns of BSE (Sensex Index) with respective Subsamples.

	Obs	JB	ADF	Q(10)
Sensex	8434	547.51	-19.09*	42.94*
BSE I	76	0.315	-3.60**	0.00
BSE II	77	0.696	-3.53**	1.21
BSE III	86	6.412**	-4.13*	0.11
BSE IV	82	13.90*	-4.45*	0.03
BSE V	84	316*	-4.07*	6.04
BSE VI	78	380*	-5.51*	0.12
BSE VI	86	7.99	-3.41**	0.03**
BSE VIII	78	29.20	-3.02***	0.02
BSE IX	82	547.51*	-4.05*	10.97*

Notes: 1) ***P-value < 0.01;**P-value < 0.05:P-value < 0.1.

2) JB represents the P-value of the Jarque-Bera test statistic for the null hypothesis of a normally distributed return series.

3) ADF represents the Augmented Dickey-Fuller test, the P-value of which confirms a stationary return series.

4) Q(10) are the Ljung-Box test statistics for return.

Source: -Authors Compilation.

2.4 Variance Ratio Test

Table 6 presents the variance ratio estimates and test statistics for RWH, assuming either homoscedasticity or heteroscedasticity for the entire sample period and the pre- and post-subsample periods, for both indices based on Lo and MacKinlay's (1988) methodology. The BSE(Sensex) full sample indicates that for shorter horizons, RWH is rejected, whereas for longer horizons it holds. For most subsamples of BSE(Sensex) and values of q, the RWH holds. Nevertheless, it appears that, for subsample VII, the period from 1st March till 31st June 2014, the evidence of random walks starts disappearing for shorter investment holding horizons. In contrast, for more extended periods it still holds. With rejection of the random walk hypothesis for the Full sample and acceptance for the rest of the subsample period, except for subsample VII, the period from 1st March to 31st June 2014. 16th parliamentary elections, which also saw the regime change in India. Given that the data are characterised by changing volatility. Based on the value of Z*(q), we conclude that the results for the full sample of BSE(Sensex) are not as strong for longer investment horizons (q=8, q=16 days), but still reject the random walk hypothesis for q=2 and q=4. Pre- and post-financial crisis results for BSE (Sensex) indicate the same level and quality of activity in the Indian market. For all the subsamples of BSE(Sensex) that are represented by the period of parliamentary elections, the random walk hypothesis holds, except that for subsample VII, for a shorter horizon, it was rejected, where inefficiency was noticed, implying predictability (weak form inefficiency). Subsample IX, for a shorter horizon reveals a significant mean revision and weak-form inefficiency. We conclude that the predictability of returns remains for shorter horizons but vanishes for longer ones as the holding period increases.

Table 6: Lo-MacKinlay Variance Ratio Test Statistics of RWH

			Number of Lags(q)			
			Q=2	**Q=4**	**Q=8**	**Q=16**
	Full Sample	**VR(q)**	1.03	1.04	1.05	1.08
		Z(q)	(3.02**)	(2.30**)	(1.38)	(1.48)
		Z*(q)	[1.79**]	[1.40]	[0.87]	[0.97]
	Subsample -I	**VR(q)**	0.988	1.042	0.992	0.828
		Z(q)	(-0.100)	(0.200)	(-0.020)	(-0.341)
		Z*(q)	[-0.809]	[0.171]	[-0.022]	[-0.339]
	Subsample -II	**VR(q)**	1.111	1.106	1.141	0.891
		Z(q)	(0.983)	(0.504)	(0.422)	(-0.217)
		Z*(q)	[1.186]	[0.560]	[0.443]	[-0.227]
	Subsample -III	**VR(q)**	0.973	0.809	0.622	0.601
		Z(q)	(-0.242)	(-0.950)	(-1.190)	(-0.844)
		Z*(q)	[-0.290]	[-0.942]	[-1.134]	[-0.822]
	Subsample -IV	**VR(q)**	1.019	1.013	0.819	0.635
BSE		**Z(q)**	(0.173)	(0.064)	(-0.556)	(-0.755)
		Z*(q)	[0.132]	[0.051]	[-0.478]	[0.697]
	Subsample -V	**VR(q)**	0.994	0.748	0.657	0.577
		Z(q)	(-0.047)	(-1.241)	(-1.066)	(-0.884)
		Z*(q)	[-0.01]	[-0.547]	[-0.574]	[-0.582]
	Subsample -VI	**VR(q)**	1.031	0.787	0.557	0.493
		Z(q)	(0.283)	(-1.011)	(-1.329)	(-1.023)
		Z*(q)	[0.419]	[-1.292]	[-1.550]	[-1.141]
	Subsample -VII	**VR(q)**	1.217	1.114	1.040	0.544
		Z(q)	(1.961**)	(0.549)	(0.123)	(-0.911)
		Z*(q)	[1.633**]	[0.473]	[0.116]	[-0.925]
	Subsample -	**VR(q)**	1.006	1.003	1.062	0.723
	VIII	**Z(q)**	(0.056)	(0.014)	(0.188)	(-0.558)
		Z*(q)	[0.046]	[0.012]	[0.178]	[-0.539]
	Subsample IX	**VR(q)**	0.621	0.500	0.432	0.199
		Z(q)	(-3.384)	[-2.390]	[-1.716]	[-1.626]
		Z*(q)	[-1.261]	[-1.040]	[-0.920]	[-1.114]

Note: 1) The variance ratios for q-day returns, VR(q) are reported in the first row.

5) Z(q) variance ratio test statistics assuming homoscedasticity, are reported in parentheses ( ).
6) Z*(q) variance ratio test statistics, heteroscedasticity-consistent, are reported in the brackets [ ]. Under the null of a random walk the variance ratio value is expected to equal one.
7) ***: Significant at the 1% level. **: Significant at the 5% level. *: Significant at the 10% level.
8) Critical values 1%-2.576, 5%-1.96 and 10% 1.645.

Source: -Authors Compilation.

Table 7: Wright Non-Parametric Variance Ratio Test Statistics of RWH using Ranks and Signs Test, Multiple Variance Ratio Test by Chow and Denning (1993)

		K	R_1	R_2	S_1	$Z_1(q)$	$Z_2(q)$
BSE	Full Sample	2	5.382*	4.501*	4.208*	3.029*	1.79
		4	3.974*	3.336*	3.447*		
		8	2.787*	2.090**	3.228*		
		16	2.406*	1.907**	3.413*		
	Subsample -I	2	-0.355	-0.176	-0.113	0.344	0.339
		4	-0.286	-0.031	0.000		
		8	-0.140	0.218	0.481		
		16	-0.340	-0.475	0.213		
	Subsample -II	2	1.039	0.946	0.000	0.983	1.186
		4	0.610	0.560	0.181		
		8	0.415	0.376	0.421		
		16	-0.399	-0.313	0.308		
	Subsample -III	2	0.578	0.141	1.393	1.190	1.134
		4	0.109	-0.387	1.432		
		8	-0.642	-0.899	0.271		
		16	-0.468	-0.628	-0.115		
	Subsample -IV	2	0.394	0.297	0.329	0.755	0.697
		4	-0.199	-0.350	0.234		
		8	-0.679	-0.519	-0.519		
		16	-0.904	-0.660	-1.165		
	Subsample -V	2	0.131**	0.375**	-0.542**	1.240	0.582
		4	-0.601**	-0.551**	-0.869**		
		8	-0.996**	-0.834**	-1.521***		
		16	-1.083**	-0.965**	-1.441***		
	Subsample -VI	2	0.002**	-0.048**	-0.562**	1.329	1.550
		4	-0.716**	-1.021**	0.060**		
		8	-0.839**	-1.273**	0.931**		
		16	-0.613**	-0.996**	1.386**		
	Subsample -VII	2	1.603	1.628	0.777	1.961***	1.633
		4	0.323	0.426	0.653		
		8	0.031	0.141	0.976		
		16	-1.009	-0.943	0.725		
	Subsample -VIII	2	-0.280	0.079	0.562	0.558	0.539
		4	-0.194	-0.089	0.721		
		8	-0.036	0.107	0.798		
		16	-0.504	-0.526	0.274		
	Subsample -IX	2	-0.276	-0.582	0.000	3.38*	1.261
		4	-0.119	-0.222	-0.597		
		8	-0.582	-0.514	-0.188		
		16	-1.321	-1.194	-0.609		

Note:1) *: Significant at the 1% level,**: Significant at the 5% level. ***: Significant at the 10% level.

2) The critical values were simulated with 10,000 replications in each case.

3) For the Chow Denning test, the 10%, 5% and 1% critical values are 2.226268, 2.490915, and 3.022202.

4) For all the cases, the values of *K* used are 2,4,8,16. Critical values 1%-2.576, 5%-1.96 and 10% 1.645.

Source: -Authors Compilation.

2.5 Wright Non-Parametric Variance Ratio Test Statistics and Multiple Variance Ratio Test.

Wright Non-Parametric Variance Ratio Test Statistics of RWH using Ranks and Signs Test and Chow-Denning Statistics are reported in Table 7. The results of the Wright Signs and Ranks test are presented. We follow (Hoque et al., 2007) rule for making inferential decisions using these statistics. If there are more than two rejections at any of the two levels of significance (1%, 5%), we reject the null of the random walk hypothesis. For the full sample of Sensex, S1 is significant, whereas R1 is significant for k=2, 4, 8, and 16, and R2 is significant for k=2 and 4. For all Sensex subsamples, S_1 is insignificant for k=2,4,8,16, R_1 for k=2,4,8,16 and R_2 for k=2,4,8,16. The full sample and Subsample V and VI of the Sensex RWH are rejected, implying that the market is weak-form inefficient. For BSE(Sensex), the Full sample of all test statistics for different holding periods is significant except for R_2 for holding periods of 8 and 16. Clearly, rank-based test statistics are overwhelmingly accepted for q's ranging from 2 to 16 of the full sample, indicating that the random walk hypothesis does not follow. For the rest of the subsamples, there is compelling evidence of the random walk hypothesis except for subsample V and subsample VI.

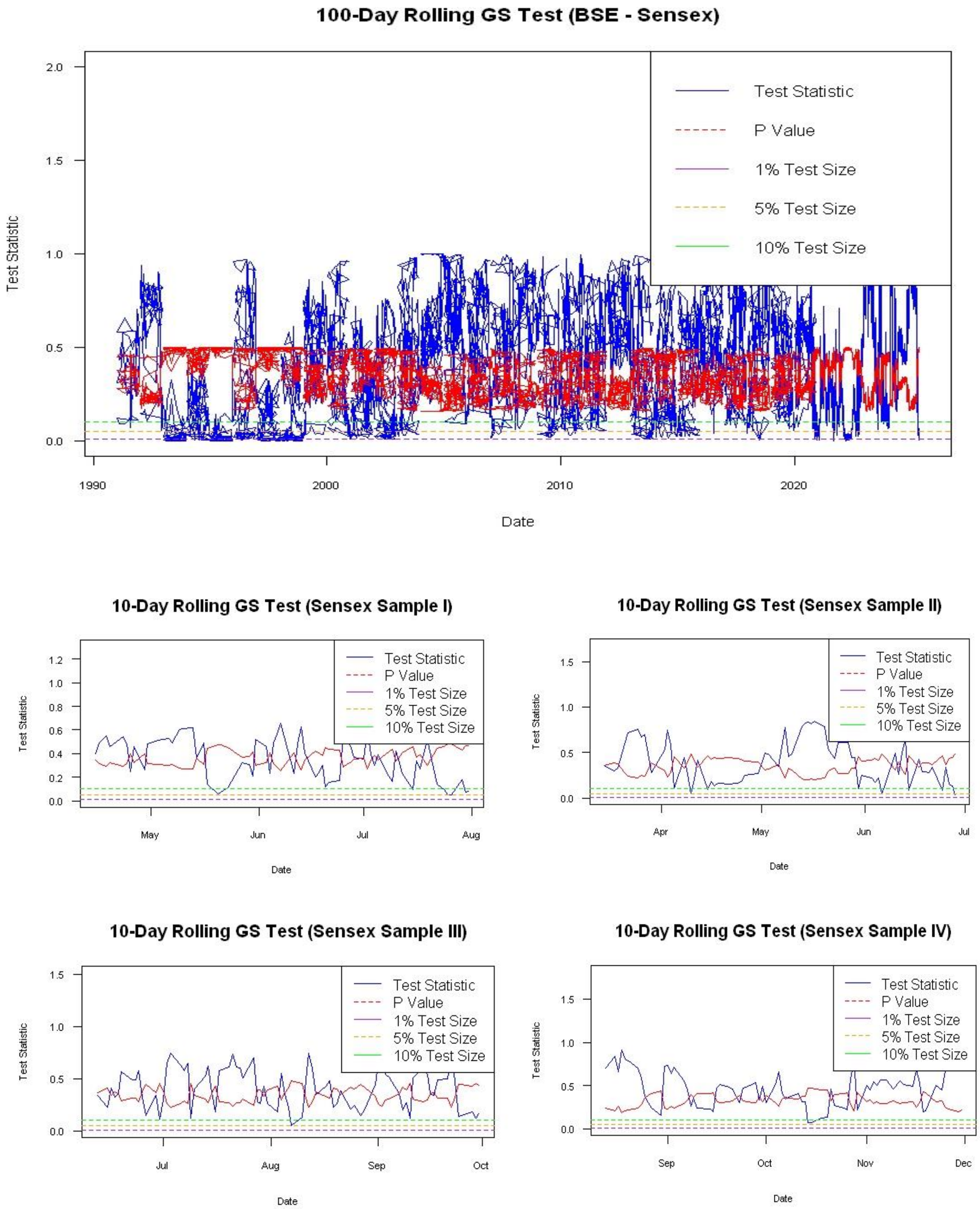
Multiple Variance Ratio Test by Chow & Denning (1993). Chow Denning test statistics are reported for both $Z_1(q)$ and $Z_2(q)$. The Chow-Denning test indicates the predictability of the Sensex's stock returns, rejecting the null of a random walk for the full sample and for subsample IX at the 1% level of significance, and for subsample VII at the 10% level of significance. The returns during the period of India's parliamentary elections tend to be random, except for subsamples IX and VII. For most of the BSE Sensex Subsamples, it indicates independence of returns.

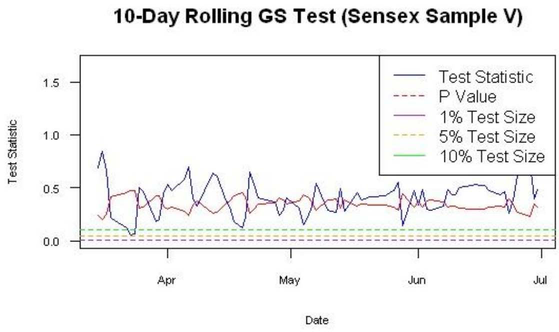
The individual and multiple variance ratio tests suggest that the Indian market moves from efficient to inefficient stages, consistent with the Adaptive Market Hypothesis.

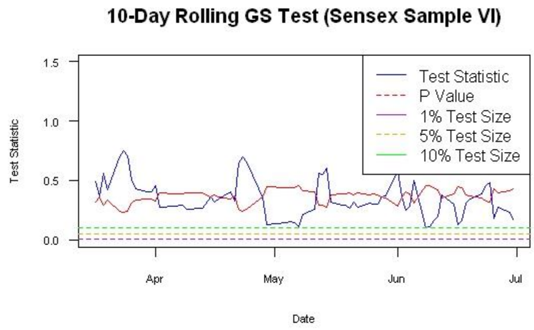
2.6 Generalised Spectral (GS) Test and Dominguez Lobato (DL) Test.

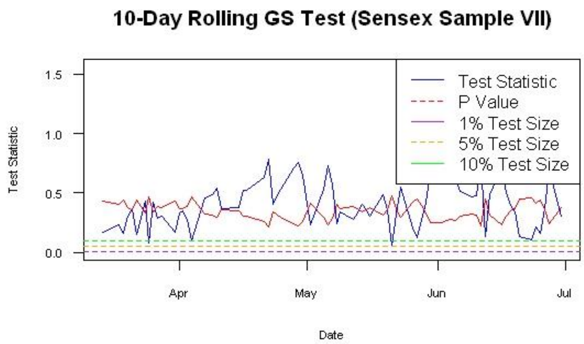
Generalised Spectral test (GS) and Dominguez Lobato test (DL) are conducted on eight Bombay Stock Exchange Sensex samples to test the evidence of evolving returns. These tests are conducted over a 10-day rolling window for the sub-sample and a 100-day rolling window for the full sample. The results of the Generalised Spectral test are graphically presented in Figure 2 for a rolling window of 10 days at 1%, 5% and 10% significance levels for all the BSE full samples and subsamples. The horizontal dotted lines parallel to the xaxis in green, orange, and purple are the 10%, 5%, and 1% critical values, respectively. The blue line represents the rolling test statistic calculated from the Generalised Spectral Test over a 10-day window for the Subsample and 100 days for the full sample. The test statistic is a measure of whether the series of returns exhibits serial correlation, which would contradict the Martingale Difference Hypothesis (MDH). The MDH posits that past returns do not predict future returns. The red line shows the p-value corresponding to each test statistic. P-values indicate the probability of observing a test statistic as extreme as the one calculated, under the assumption that the null hypothesis (MDH) is accurate. A lower p-value suggests more substantial evidence against the null hypothesis. Sample I: The test statistic crosses the green line (significance level) in June and at the end of August, suggesting that past returns have predictive power over future returns, contradicting the MDH. In Samples II, May, and July, the test statistic indicates that the prediction of future returns was possible, contradicting the MDH. Both Sample I and Sample II showed predictability in returns in the second and last months of the parliamentary election, suggesting a close relationship between the 10^{th} and 11^{th} parliamentary elections. Sample III and Sample IV return predictions were possible in the third month, suggesting inefficiency and a close relationship between the 12th and 13th parliamentary elections. Sample V indicates the market was inefficient in the first month, and subsequently, the next two months saw spikes in test statistics, suggesting the market moved toward inefficiency. Still, the significance levels do not confirm this. Sample VI observed the market being inefficient for a few days in May and July, during which the return prediction was possible multiple times. Sample VII market moved towards inefficiency numerous times in the first month, though we cannot confirm it because the test statistic does not cross the significance level. In the third month (May), the prediction of returns(inefficiency) was possible. The fourth month saw the market move towards inefficiency, though it did not cross the significance level. Sample VIII market moved towards inefficiency every month, though it was inefficient only at the end of the month(July). The test statistic was reported as significant for the entire sample period under study. The 10th, 11th, and 12th, 13th parliamentary elections share a close relationship, as the predicted returns were in similar months.

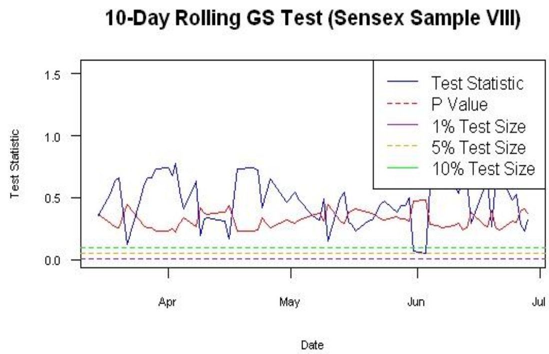
Figure 2: Generalised Spectral Test Statistics for the BSE Sensex and Subsample (100-day and 10-day rolling window).











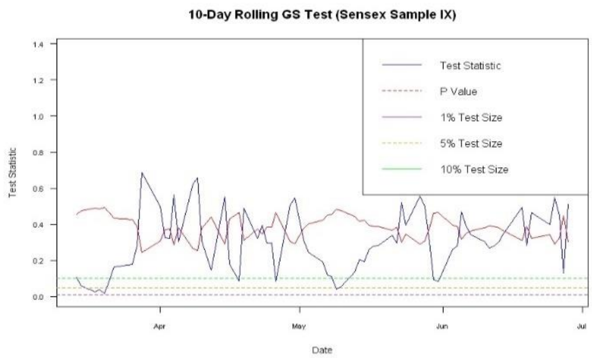
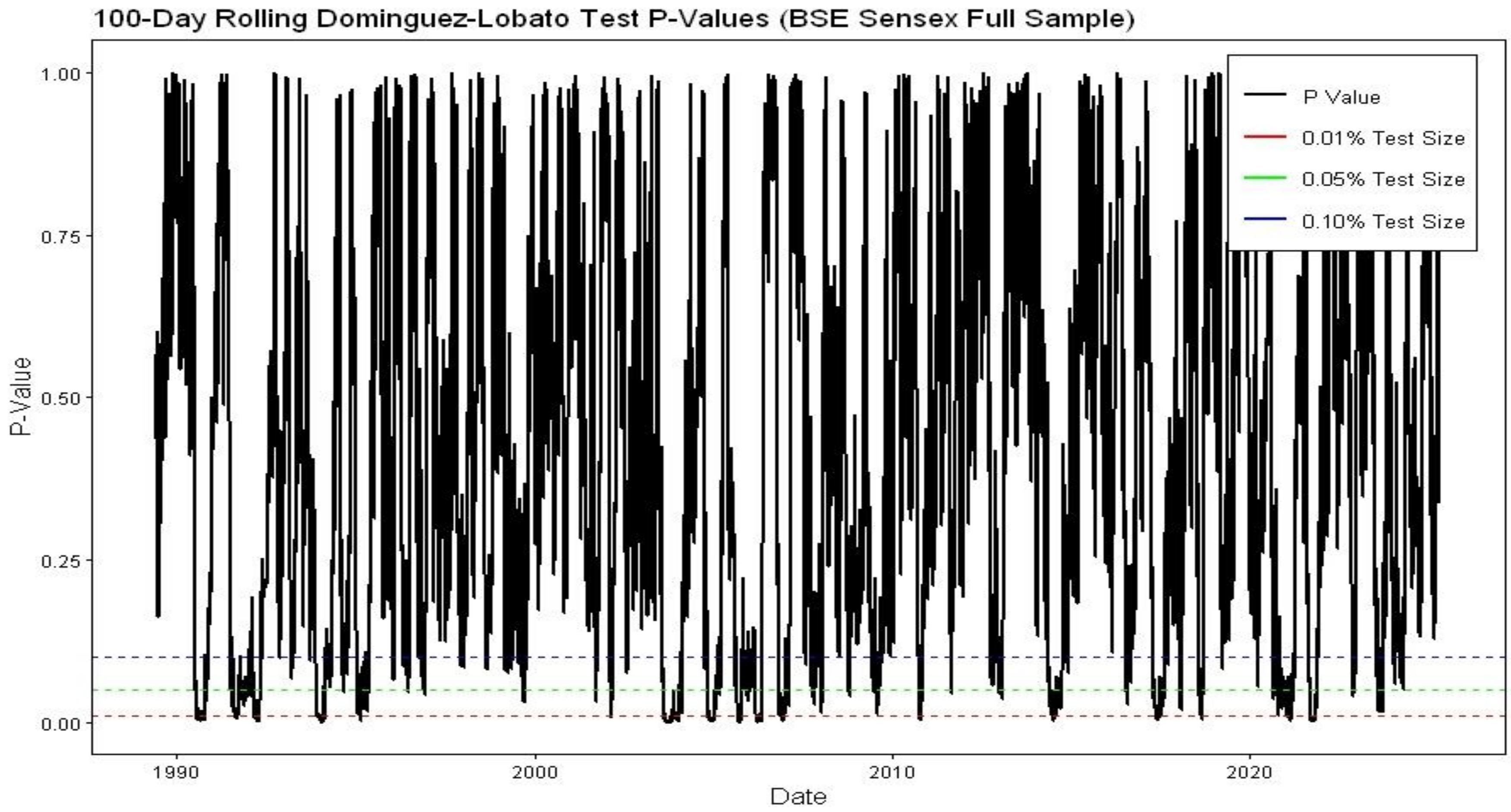
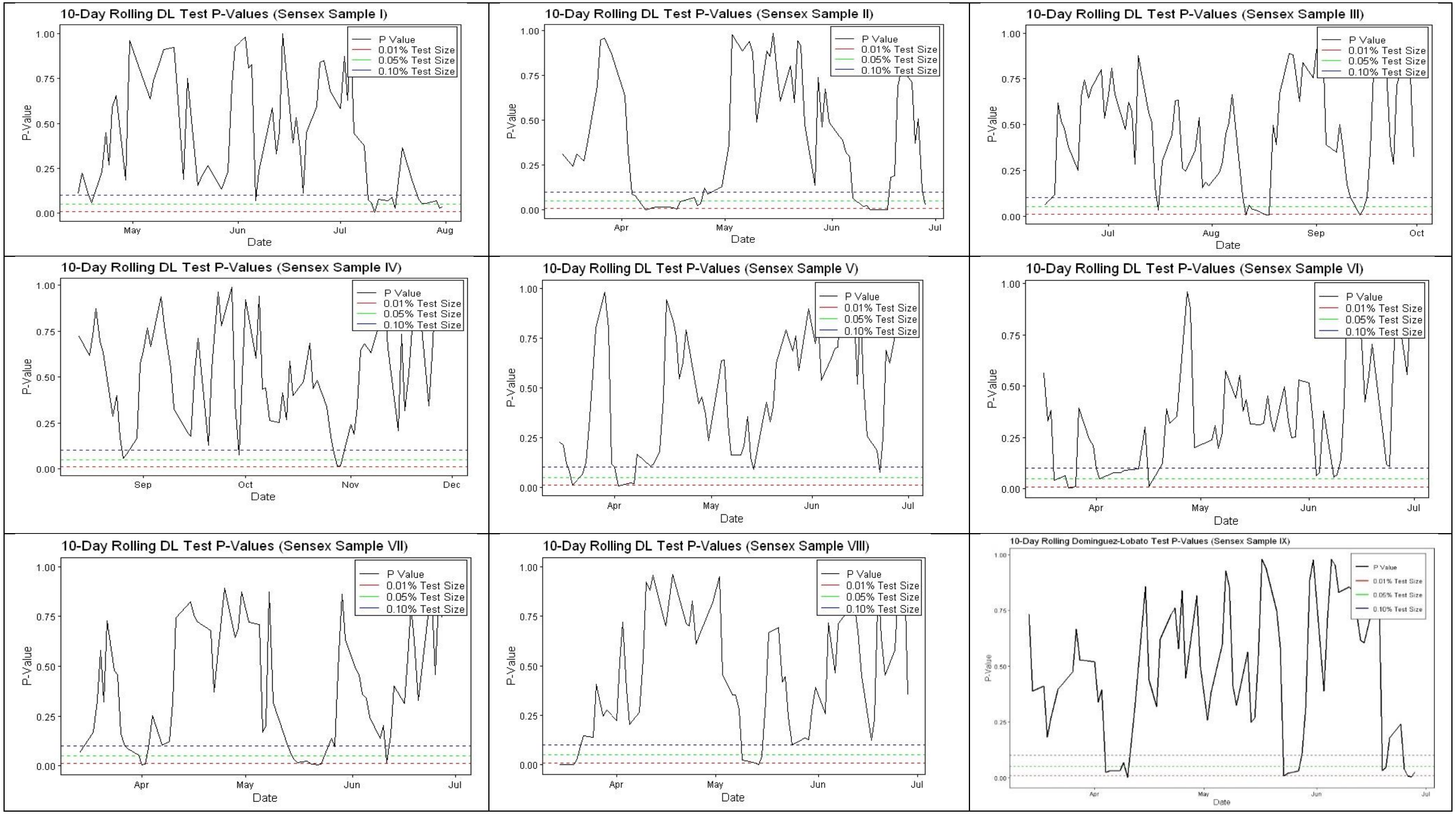


Figure 3 graphically represents the result of the Dominguez Lobato Test (DL). For the BSE full sample, the structure of the p-values reveals the moment of market from the efficiency to the inefficiency phase. In every decade, there are at least five short periods where the market tends to be highly efficient. DL test for sample I show a heightened period of efficiency from May till July and inefficiency at the beginning and end of August. Sample II: The market is efficient in the first month after the election code is announced. The next month may be characterised by inefficiency, followed by efficiency in June, then inefficiency-efficiency and inefficiency in July. The first two parliamentary elections ended with inefficiency after four months. Sample III started with inefficiency at the beginning of the first month, followed by a few days of inefficiency in August, then again, a few days of inefficiency in September and October, ending with the market being efficient at the end of the four-month election period. Sample IV started with an efficient period, then a few days of inefficiency in September, October, and November and ended with an efficient market at the end of four months of the parliamentary election. Sample III and Sample IV ended with an efficient market at the end of four months of the election phase/code. Sample V started with a volatile phase of efficiency and inefficiency in April, with a short-lived efficiency peak at the end of the month, followed by inefficiency at the end of April and the beginning of May. For the rest of the period, the market was efficient, with only a few sporadic days in June and July when it was inefficient. Sample VI with the imposition of the election code and the start of the parliamentary elections market fell from the efficient phase to inefficient again, recovering back to the efficiency phase in April, from where it fell back to the inefficient phase and continued till the entire month's end of May end of May, which continued for the whole of June. July started with an inefficient market and ended with an efficient one. Both Sample V and VI saw the market start in an efficient phase and end in efficiency. Sample VII showed the market starting inefficiently in April and then moving towards efficiency by the end of April. The entire month of May saw the market efficient, then slightly moving towards inefficiency in the middle of June, recovering to efficiency at the end of June, and then moving back to efficiency. Starting with a few days of inefficiency, the entire period of July was efficient. Sample VIII saw the market starting with inefficiency, then moving towards efficiency, then again towards inefficiency for a few days in May, and then, for the entire period till the end of the election code/parliamentary election, the market was in the efficient stage. In both Sample VII and Sample VIII, the market initially became efficient, then moved towards inefficiency in the third month, and returned to efficiency at the end of the parliamentary elections. For the last three parliamentary elections, i.e., 16th, 17th, and 18th, the month between May and June saw a few days (probably a week) when the market was efficient. Various political events during the election code period may have coincided with phases of efficiency and inefficiency, as similar studies (Charles et al., 2012; Hiremath & Kumari, 2014; Khuntia & Pattanayak, 2018) have reported that such events can influence the dynamics of efficiency. Dominguez Lobato's test statistics report that efficiency and inefficiency evolve. Predicting returns was possible for every parliamentary election under study, from the 10th to the 18th.

Figure 3: Dominguez Lobato P-Value of BSE Full sample and Subsample (100-day rolling window for Full sample and 10 days for Subsample).




10-Day Rolling DL Test P-Values (Sensex Sample I)
10-Day Rolling DL Test P-Values (Sensex Sample II)
10-Day Rolling DL Test P-Values (Sensex Sample III)
10-Day Rolling DL Test P-Values (Sensex Sample IV)
10-Day Rolling DL Test P-Values (Sensex Sample V)
10-Day Rolling DL Test P-Values (Sensex Sample VI)
10-Day Rolling DL Test P-Values (Sensex Sample VII)
10-Day Rolling DL Test P-Values (Sensex Sample VIII)
10-Day Rolling Dominguez-Lobato Test P-Values (Sensex Sample IX)
P Value
0.01% Test Size
0.05% Test Size
0.10% Test Size
P-Value
Date
1.00
0.75
0.50
0.25
0.00
May
Jun
Jul
Aug
Apr
Sep
Oct
Nov
Dec

Chapter 3

Information Efficiency and its consistency with AMH.

3.1 Introduction

This section examines the evolution of information efficiency in the Indian equity market by analysing the BSE Sensex and NSE Nifty indices using descriptive statistics, STL decomposition, and multifractal analysis via the Generalised Hurst Exponent framework. These techniques help capture distributional properties, seasonal and structural patterns, and the degree of multifractality embedded in returns—each of which provides insights into how market efficiency changes over time. In addition to the full-sample analysis, the same methods are systematically applied to all election-linked subsamples, allowing a comparative assessment of efficiency across different market conditions.

The descriptive statistics highlight deviations from normality and the presence of autocorrelation, signalling potential return predictability and inefficiency in certain periods. STL decomposition allows the extraction of trend, seasonal, and irregular components, revealing structural shifts and high-frequency fluctuations linked to major economic and financial events. Finally, the Generalised Hurst Exponent and MF-DFA results quantify the multifractal behaviour of returns, showing variations in persistence, anti-persistence, and complexity across subsamples.

Overall, the combined evidence supports the idea that market efficiency is dynamic rather than static, aligning with the core premise of the Adaptive Market Hypothesis (AMH)—that efficiency fluctuates in response to changing market conditions, investor behaviour, and external shocks.

Table 8: Descriptive Statistics of BSE(Sensex) and NSE(Nifty) Returns.

Statistics	BSE(Sensex)	NSE(Nifty)
Mean	0.00068	0.00066
SD	0.01582	0.01559
Skewness	0.06150	0.05675
Kurtosis	10.7916	11.9300
JB	0*	0*
Ljung-Box Q	8.799628e-13*	0*
Obs.	8435	8126

Notes: 1) "Obs." – Observation.
2) *P-value < 0.01.
3) SD represents Standard Deviation.
4) JB represents the P-value of the Jarque-Bera test statistic for the null hypothesis of a normally distributed return series.

Source: -Authors Compilation.

3.2 Descriptive Statistics

Both the BSE Sensex and the NSE Nifty have positive means, indicating that, on average, the stock market returns are slightly positive. However, the difference between the means is minimal (0.00068 for BSE and 0.00066 for NSE), suggesting similar average returns for both indices. Standard deviation measures the dispersion of returns around the mean. Both BSE Sensex and NSE Nifty have identical standard deviations (0.01582 for BSE and 0.01559 for NSE), indicating comparable volatility levels. Skewness measures the symmetry of the distribution of returns. Both BSE Sensex and NSE Nifty have positive skewness values (0.06150 for BSE and 0.05675 for NSE), indicating a slightly right-skewed distribution where the tail on the right side is more extended. Kurtosis measures the "tailedness" of the distribution of returns. Both the BSE Sensex and the NSE Nifty have high kurtosis values (10.7916 for BSE and 11.9300 for NSE), indicating heavy tails relative to a normal distribution. This suggests that extreme events (both positive and negative) are more likely to occur than in a normal distribution. A JB value of 0 indicates that the distribution is perfectly normal, suggesting that their returns do not significantly deviate from a normal distribution. The Ljung-Box Q tests the null hypothesis that the data are independently distributed. Both BSE Sensex and NSE Nifty have extremely low p-values (8.799628e-13 for BSE and 0 for NSE), indicating rejection of the null hypothesis. This suggests significant autocorrelation in the returns of both indices.

3.3 STL Decomposition

Figures 4 and 5 present the results of STL decomposition of the index returns into three constituent elements of the BSE Sensex market index and the NSE Nifty market index. The seasonal (Figure 4b,5b), trend (Figure 4c,5c), and remainder (Figure 4d,5d). Figures 4 & 5 display the patterns observed in the stock market index returns over time. We can clearly see a yearly cycle, indicating a seasonal trend in the data. However, the trend component of the data does not exhibit significant changes over time. Its variability is minimal, with very little fluctuation observed. On the other hand, the remainder component shows irregular fluctuations, suggesting that other factors beyond seasonal patterns influence stock market behaviour. For instance, events such as the Asian Financial Crisis of 1997, the Dot-com bubble of 2000, the Global Financial Crisis of 2008, and COVID-19 of 2020 may contribute to these high-frequency fluctuations. The remainder component appears noisy; it is important to note that this noise is not purely random. Instead, it likely stems from various macroeconomic factors influencing the stock market beyond seasonal cycles. By isolating the remainder component and subjecting it to MF-DFA analysis, we gain insights into the specific, dynamic characteristics of the fluctuations within the stock returns.

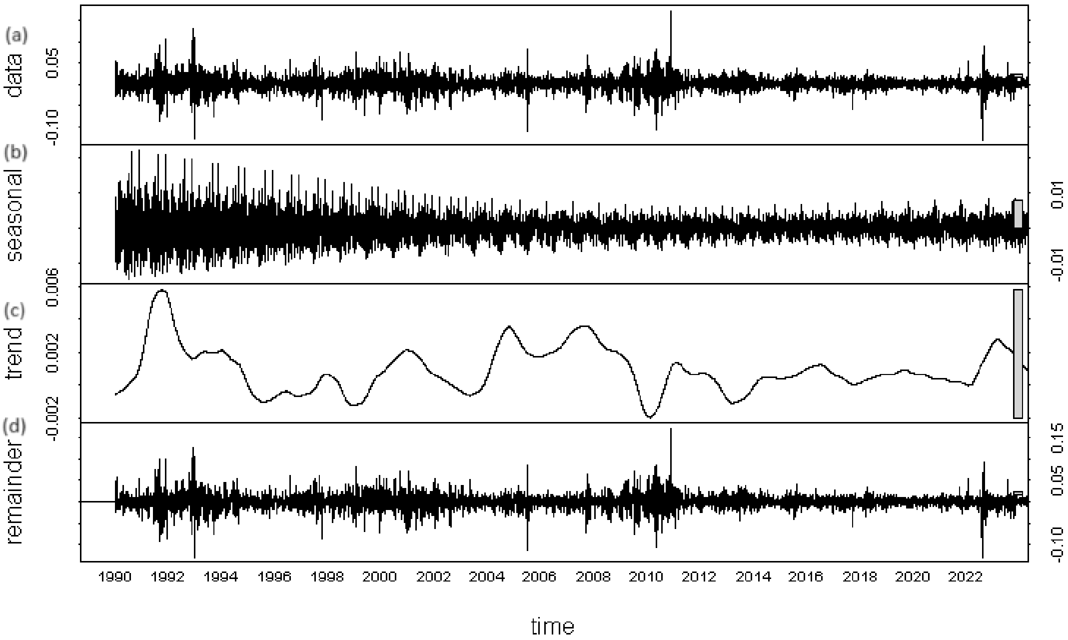


Figure 4: STL Decomposition of Index Returns time series (BSE Sensex Stock Market Index). (a) The original time series, (b) Seasonal Component, (c) Trend Component, (d) Remainder Component

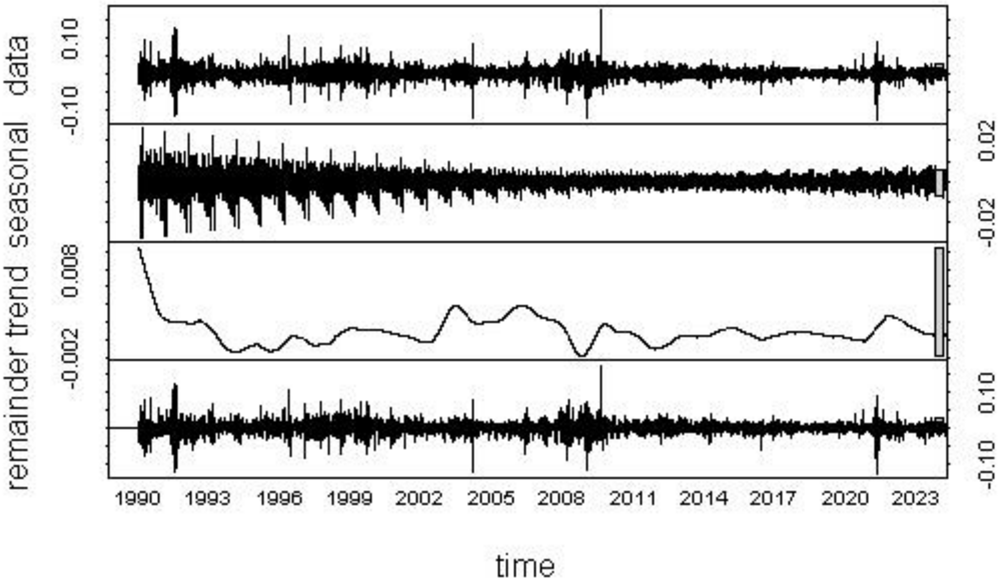


Figure 5: STL Decomposition of Index Returns time series (NSE Nifty Stock Market Index). (a) The original time series, (b) Seasonal Component, (c) Trend Component, (d) Remainder Component.

3.4 Generalised Hurst Exponents

Table 9: Generalised Hurst Exponents for BSE Sensex, NSE Nifty, and various Sub-samples of BSE

Order q	Sensex	Nifty	BSE I	BSE II	BSE III	BSE IV	BSE V	BSE VI	BSE VII	BSE VIII	BSE IX
-10	0.55	0.57	2.83	3.15	2.37	3.97	2.44	2.48	2.68	2.44	3.58
-8	0.54	0.56	2.80	3.12	2.35	3.95	2.42	2.46	2.66	2.42	3.57
-6	0.52	0.54	2.76	3.08	2.32	3.91	2.38	2.43	2.62	2.39	3.56
-4	0.51	0.52	2.68	3.00	2.28	3.83	2.34	2.38	2.57	2.35	3.56
-2	0.50	0.50	2.54	2.83	2.24	3.60	2.29	2.32	2.52	2.32	3.65
0	0.49	0.50	4.37	4.53	4.66	3.82	2.57	3.62	3.26	4.05	3.78
2	0.46	0.48	0.96	0.29	0.74	0.39	0.29	0.34	0.34	0.53	0.23
4	0.41	0.43	0.83	0.18	0.64	0.19	0.14	0.13	0.22	0.44	-0.07
6	0.37	0.38	0.78	0.14	0.61	0.11	0.08	0.04	0.16	0.41	-19
8	0.33	0.36	0.75	0.11	0.58	0.06	0.05	-0.00	0.12	0.38	-0.24
10	0.31	0.33	0.73	0.10	0.57	0.03	0.03	-0.02	0.10	0.37	-0.27
Δh	0.24	0.24	-2.1	-3.05	-1.8	-3.94	-2.41	-2.5	-2.58	-2.07	-3.85

Note: 1) Indices range over q∈ [-10,10].

2) BSE-Bombay Stock Exchange; BSE Subsamples are indicated as BSE I, BSE II and so on.

Source: - Author Compilation.

Table 9 presents the estimated Generalised Hurst Exponents for the BSE Sensex, NSE Nifty, and their respective subsamples over the range q ∈ [–10, 10]. For both major indices, h(q) exhibits a clear decreasing pattern as q increases, indicating strong multifractality in the time series. This behaviour suggests that the underlying return dynamics are influenced by a combination of long-range correlations and fat-tailed return distributions, consistent with the complex and evolving nature of financial markets. The multifractal spectrum width (Δh) is identical for the Sensex and Nifty at 0.24, implying that both markets possess a similar degree of multifractal structure and, therefore, exhibit comparable levels of informational efficiency.

Using the classical Hurst exponent at q = 2, both the BSE Sensex and NSE Nifty show values below 0.5, indicating anti-persistent behaviour. This means that positive returns tend to be followed by negative returns and vice versa, reflecting rapid corrections and suggesting that the market incorporates information efficiently, in line with weak-form efficiency under the Adaptive Market Hypothesis (AMH). The presence of anti-persistence further supports the idea that price movements are mean-reverting in the short run.

A comparison across the BSE subsamples reveals substantial variation in Δh values, indicating that multifractality—and thus efficiency—varies over time. Subsample III shows the smallest degree of multifractality, suggesting it is the most efficient period, likely characterised by stable market conditions and improved information flow. In contrast, Subsample IX displays the highest multifractal width, reflecting the least efficient period, possibly corresponding to heightened volatility, market stress, or structural breaks. The negative or unusually high values of h(q) for large q in certain subsamples (e.g., BSE IX) further indicate periods dominated by extreme fluctuations, reinforcing the adaptive nature of market behaviour. Overall, these findings highlight that market efficiency is not constant but evolves over time, consistent with the AMH framework.

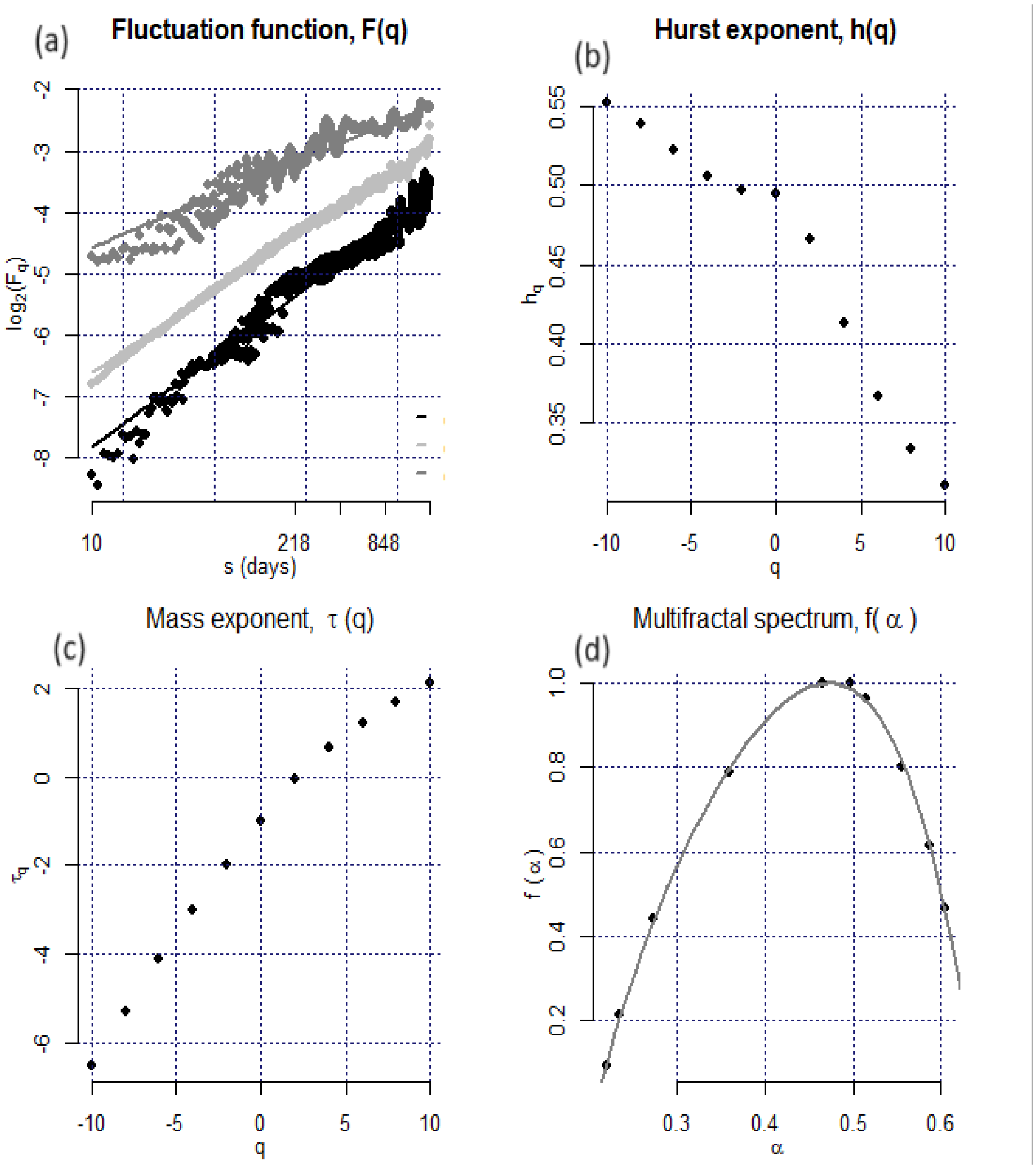


Figure 6: The MF-DFA results of the BSE Sensex Market Index Returns. (a) Fluctuation functions for q=-10, q=0, q=10. (b) Generalised Hurst Exponent for each *q*. (c) Rényi exponent, *τ*(q). (d) Multifractal spectrum.

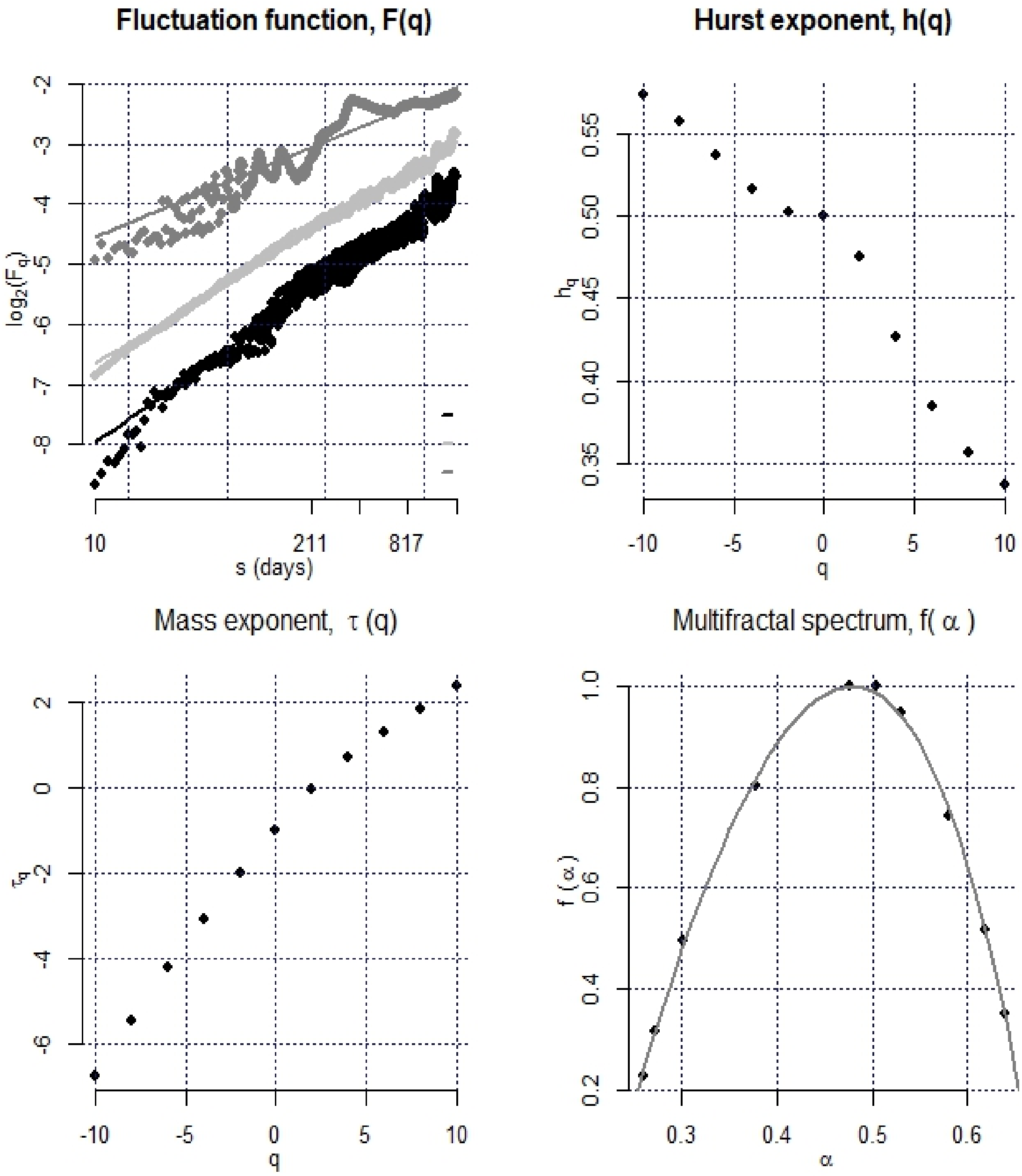


Figure 7: The MF-DFA results of the NSE Nifty Market Index Returns. (a) Fluctuation functions for q=-10, q=0, q=10. (b) Generalised Hurst Exponent for each *q*. (c) Rényi exponent, τ(q). (d) Multifractal spectrum.

Chapter 4

Time-varying Inefficiency of the Indian Stock Market.

4.1 Introduction

This section investigates how the degree of market inefficiency in the Indian equity market evolves over time by analysing daily returns of the BSE Sensex and its corresponding election-based subsamples. Using descriptive statistics, moving-window autocorrelation, and a state-space modelling framework, the analysis captures variations in return behaviour, predictability, and structural shifts across different political and economic regimes. These methods collectively allow us to examine whether inefficiencies are persistent, temporary, or sensitive to major events such as parliamentary elections, crises, or policy transitions. The evidence highlights that market efficiency is not constant but fluctuates dynamically, consistent with the central premise of the Adaptive Market Hypothesis (AMH).

4.2 Descriptive Statistics

Table 10 presents the descriptive statistics of BSE Sensex daily returns and their subsamples. The overall mean return of the Sensex is close to zero (0.000559). The standard deviation (0.015826) indicates a daily volatility of approximately 1.6%. The minimum is (-14.1%), and the maximum (15.9%) suggests the presence of rare but large market shocks. Subsamples I, II, and VIII, characterised by low skewness and kurtosis closer to normal, indicate that the periods of parliamentary elections were stable. Subsample V and IX, with negative mean, strong left skewness and high kurtosis, indicate crisis-like periods. Subsample V saw a regime change, whereas subsample IX's ruling party lost an unexpected no of seats in the lower house. Subsample IV is characterised by near-zero returns, mild positive skewness, and moderate leptokurtosis, suggesting calm with occasional large shocks. Subsample VI: (March 1 to June 30 2009 – 15th Parliamentary Election), a period just after the 2008 financial crisis, with a positive mean value of (0.006681), right skewness with value (2.06443), and kurtosis around (12.77314), indicated a boom phase of parliamentary elections.

Table 10: Descriptive Statistics of BSE (Sensex) and various Subsamples

	Mean	SD	Min	Max	N	Skewness	Kurtosis
BSE (Sensex)	0.000559	0.015826	-0.14102	0.1599	8434	-0.16752	10.62551
Subsample I	0.004122	0.016925	-0.04229	0.045826	76	0.05178	3.27180
Subsample II	0.001419	0.013419	-0.02715	0.037145	77	0.19392	2.84879
Subsample III	-0.00187	0.02157	-0.05985	0.073141	86	0.25441	3.94199
Subsample IV	0.000343	0.016141	-0.03989	0.054958	82	0.37099	4.79858
Subsample V	-0.00231	0.022471	-0.11809	0.079311	84	-1.41114	12.00787
Subsample VI	0.006681	0.028034	-0.04898	0.1599	78	2.06443	12.77314
Subsample VII	-0.00187	0.02157	-0.05985	0.073141	86	0.25441	3.94199
Subsample VIII	0.001133	0.008434	-0.01391	0.036801	78	0.85799	5.50655
Subsample IX	0.001211	0.010324	-0.05912	0.03334	82	-1.73103	17.19202

Note: N denotes the number of observations. BSE-Bombay Stock Exchange.
Source: -Authors Compilation.

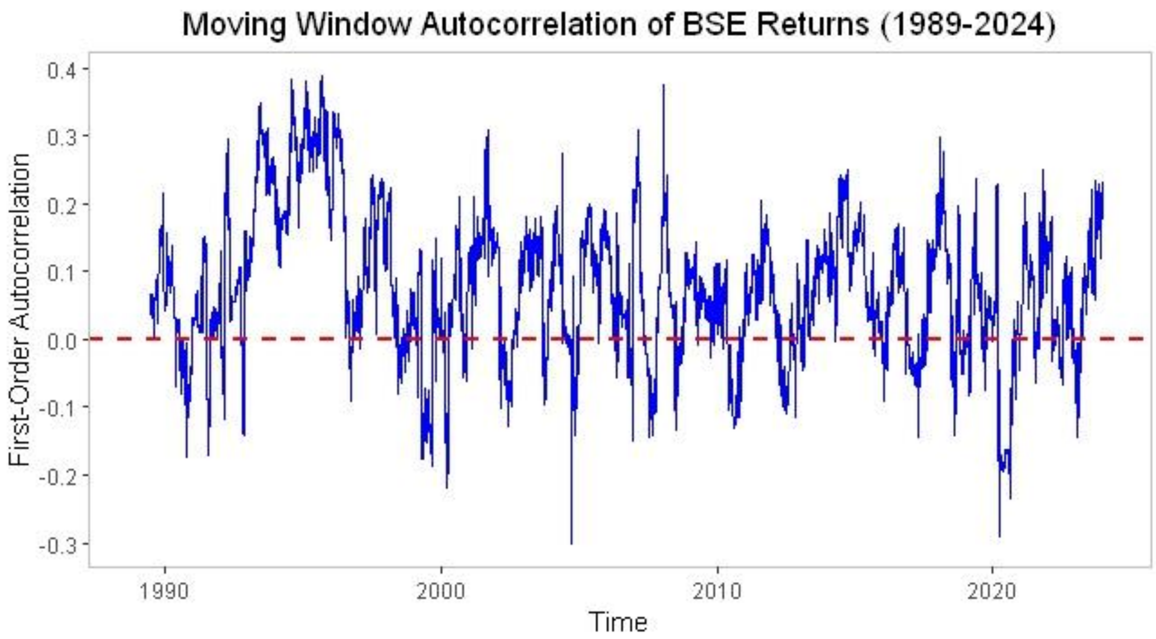


Figure 8: Moving Window Autocorrelation of BSE Sensex Returns varying through time by applying first-order Autocorrelation. The window width is 100.
Source: -Authors Compilation.

4.3 Moving Window Autocorrelation

The result of the moving window first-order autocorrelation is exhibited in Figure 8. It shows the time-varying structure of the market. It also implies that the degree of market efficiency varies through time, as the return series may contain a unit root. The Augmented Dickey-Fuller (ADF) test is used to determine whether a time series exhibits a unit root. A model with a time trend and a constant was applied. We use the Schwarz Bayesian Information Criterion (SBIC) as a criterion for selecting the order. Lag 0 is chosen, and the test statistic is computed to be 0.3541, at which the corresponding 5% critical value is -3.41. Thus, we cannot reject the null hypothesis that the data contain a unit root. These also support our assumption that the AR Coefficient is a time-varying AR model and follows a random walk process.

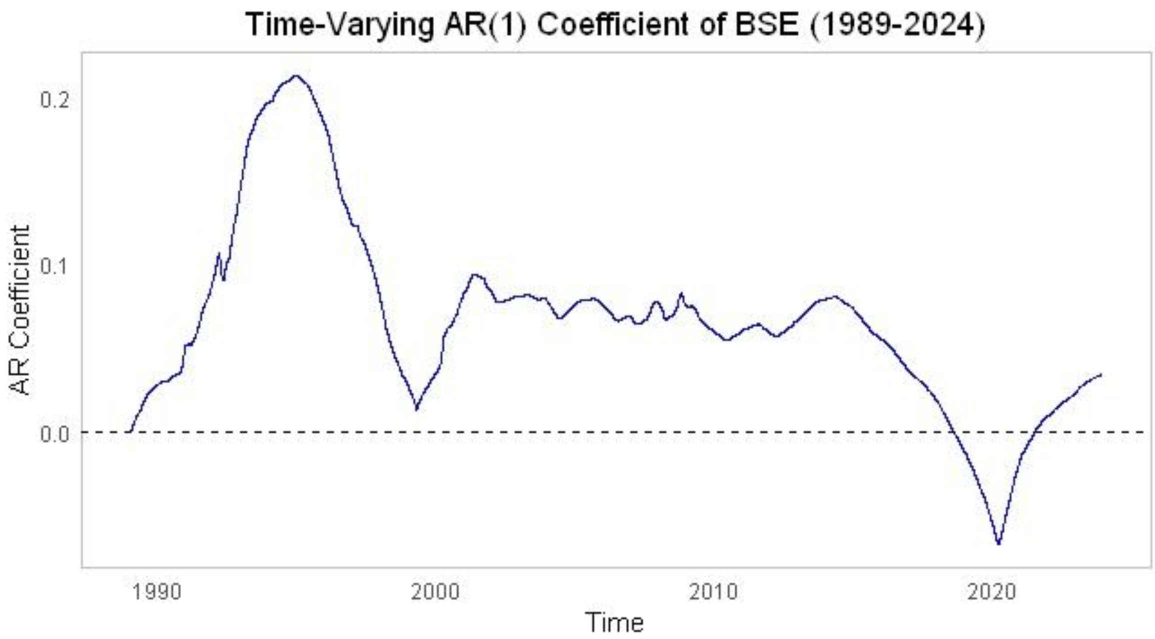


Figure 9: Time-varying Market Inefficiency in the Indian Stock Market (BSE Sensex Index). Window width is 100 for Autocorrelation.
Source: -Authors Compilation.

4.4 State Space Model

We apply the model discussed in the previous section to daily Index returns of the BSE Sensex index. We set the initial values for both the state variable and the returns data to zero. A state variable being zero means the market is completely efficient. We verify the robustness of the estimation results by varying the initial values of the state variables. Estimating state variables over time can be viewed as the market's path toward efficiency. It indicates that past inefficiencies gradually adjust over time.

Table 11: Rule to interpret AR(1) Coefficient (Based on Tsay (n.d.), Poterba et al. (1987), Lo & Mackinlay (1988), De Bondt & Thaler (1985)).

AR(1) Coefficient	Market Behaviour	Interpretation
≈ 0	Efficient Market	No Predictability, Price follows a random walk
> 0	Momentum	Trend following behaviour
< 0	Mean-reversion	Returns tend to reverse, and possibly predictability
≪ 0	Overreaction, Herding	Possible irrational behaviour, speculative signs.

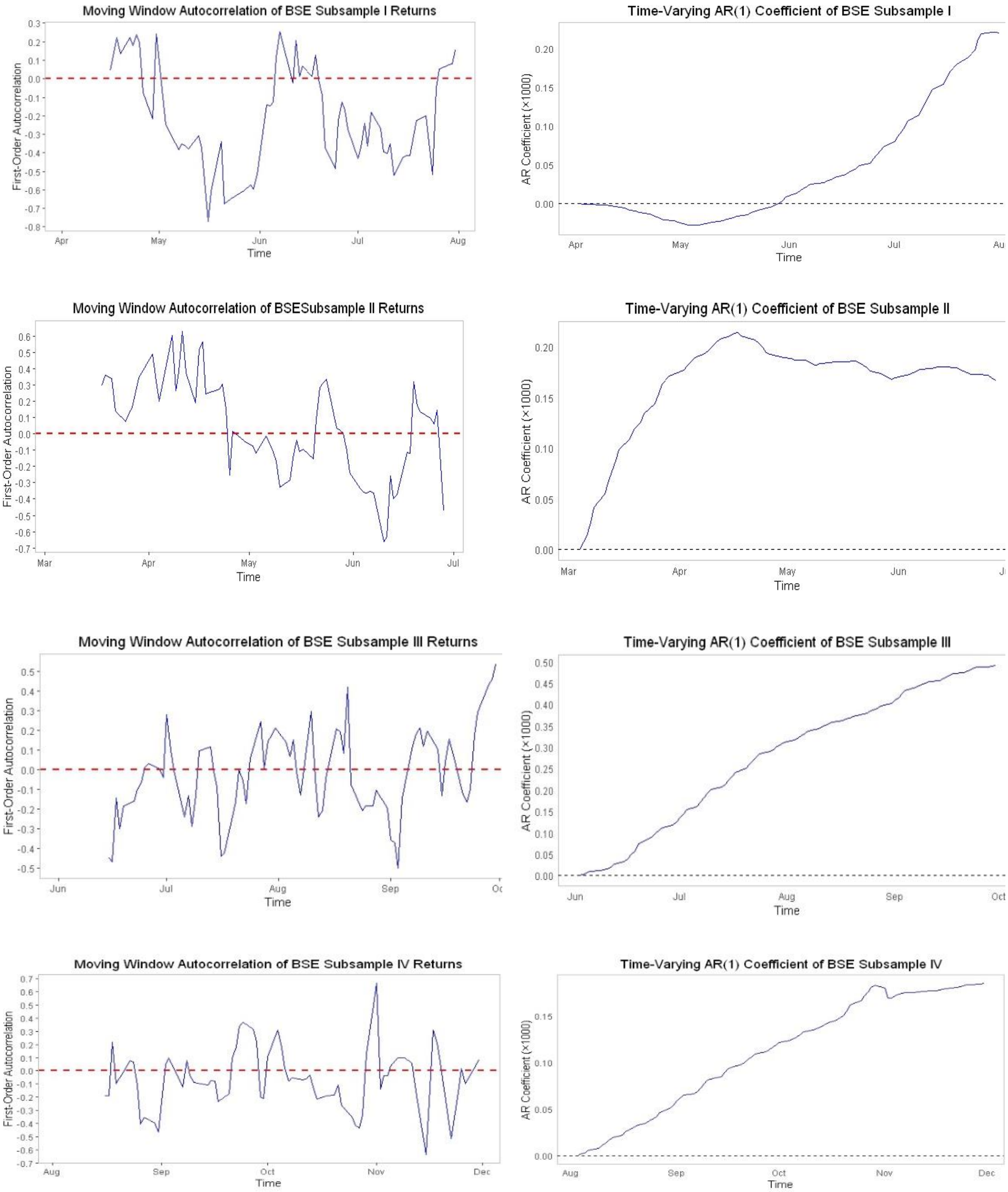
Source: -Authors Compilation.

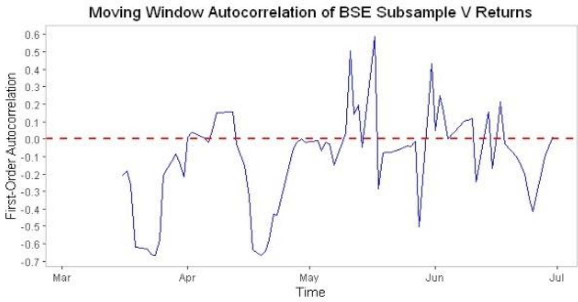
Figure 9 shows that the estimated AR coefficients vary over time and that the graph's shape is similar to the autocorrelation estimated using the moving-window method. Therefore, we can see that the degree of market inefficiency varies through time. In the 1990s, the estimated coefficients were relatively low. In 1995, the estimated coefficient reached its highest level during the entire sample period. Thus, we assume that the Indian stock market was relatively inefficient during this period. It is also a phase when the Indian government introduced the LPG (Liberalisation, Privatisation and Globalisation) policy. Subsequently, it starts falling from 1995, stabilising in 2000. Further, the estimated coefficient remains constant from 2000 to 2015. After 2015, the market began to decline, reaching a negative point during the COVID-19 pandemic. It indicates excessive market overreaction, implying that price movements are not only predictable but also disproportionately reverse, which is a sign of speculative behaviour and herding in the market (De Bondt & Thaler, 1985). Thus, we conclude that the Indian Stock market became the most efficient before the start of the COVID-19 pandemic.

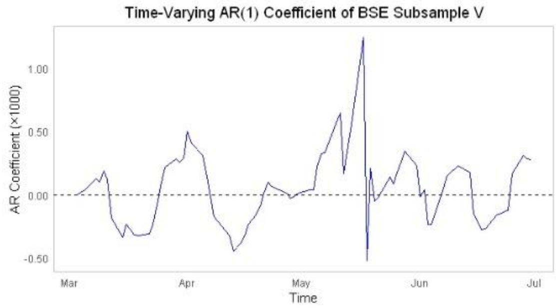
Figure 10 presents the analysis of various subsamples in chronological order. Subsample I: 10th Parliamentary Elections, the period from April 1 1991, till July 31 1991. In the first month of subsample I, it was efficient; subsequently, for May, the returns were possibly predictable. Once the results were declared on June 21 1991. The market showed trend-following behaviour. LPG[*] policy, also known as the New Economic Policy, was introduced in India on July 24, 1991. These could be the reasons for the market's momentum, suggesting inefficiency. Similar results were also observed by Kołatka (2020b) for the Polish stock index WIG, following the transformation of the economic system from 1997 to 2001.

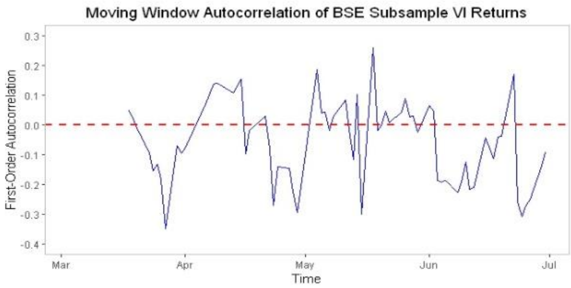
From Subsample II to Subsample IV, the market tends to be highly inefficient during parliamentary elections, suggesting trend-following behaviour. Subsample V, a period from March 1 to June 30, 2004 – 14th Parliamentary Election, the market was highly efficient, although it deviated from both efficiency and inefficiency. It also saw a regime change: the UPA defeated the NDA government. Subsample VI and Subsample VII witnessed the market transitioning from efficiency to inefficiency, although in the last month, following the announcement of the results, it shifted towards efficiency. Subsample VII witnessed a sharp shift towards efficiency; it was a period marked by another regime change. The result was also reported by Patra & Hiremath (2024), who noted that efficiency increased due to the influence of universal and global events. Subsample VIII - March 1 to June 1, 2019 – 17th Parliamentary Election. The market exhibited irrational behaviour towards the end of the election phase. Subsample IX: 1st March 2024 to June 30, 2024. The results were unexpected, as they resulted in the ruling party and its coalition losing a majority in the lower house. The market transitioned from a period of inefficiency to efficiency from March to May. As the election results were announced in June, the market experienced a sharp decline, suggesting overreaction and herding behaviour.

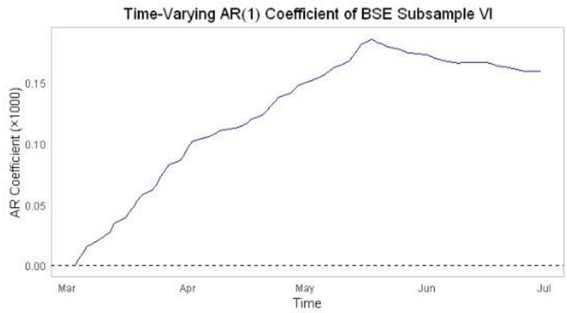
Figure 10: First-order Autocorrelation of the Subsample return series and Time-varying Market Inefficiency during the various phases of Parliamentary Elections. The window width is 10 for Autocorrelation.

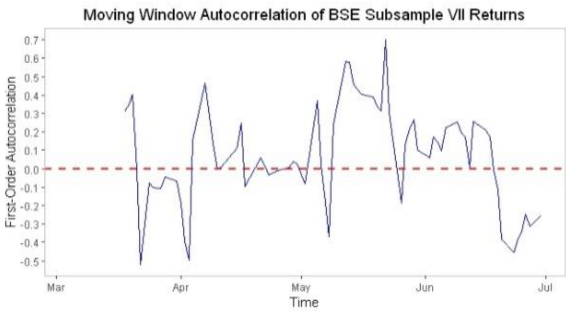


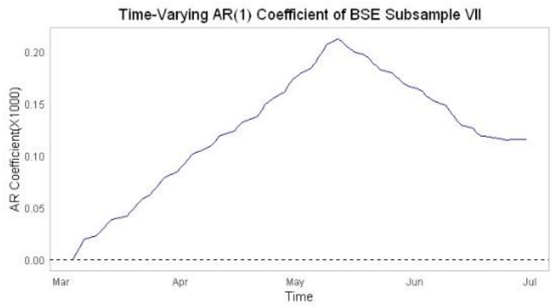

Moving Window Autocorrelation of BSE Subsample V Returns
First-Order Autocorrelation
Mar
Apr
May
Jun
Jul
Time


Time-Varying AR(1) Coefficient of BSE Subsample V
AR Coefficient (×1000)
Mar
Apr
May
Jun
Jul
Time


Moving Window Autocorrelation of BSE Subsample VI Returns
First-Order Autocorrelation
Mar
Apr
May
Jun
Jul
Time


Time-Varying AR(1) Coefficient of BSE Subsample VI
AR Coefficient (×1000)
Mar
Apr
May
Jun
Jul
Time


Moving Window Autocorrelation of BSE Subsample VII Returns
First-Order Autocorrelation
Mar
Apr
May
Jun
Jul
Time


Time-Varying AR(1) Coefficient of BSE Subsample VII
AR Coefficient(X1000)
Mar
Apr
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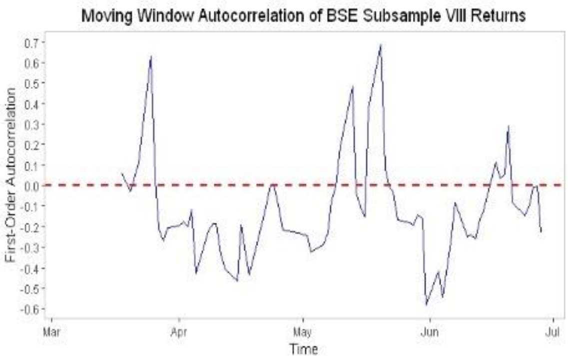
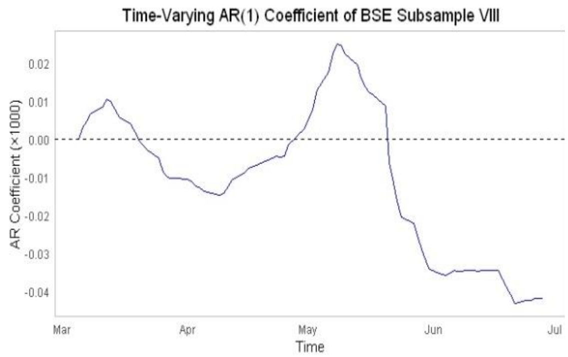
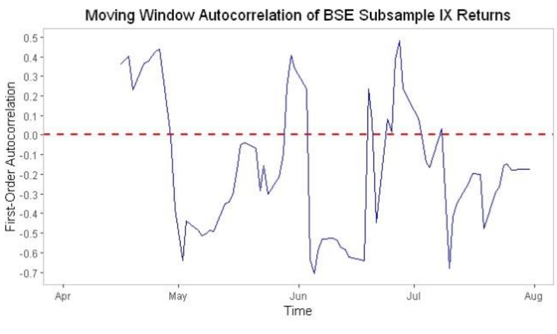
Time


Moving Window Autocorrelation of BSE Subsample VIII Returns
First-Order Autocorrelation
Mar
Apr
May
Jun
Jul
Time


Time-Varying AR(1) Coefficient of BSE Subsample VIII
AR Coefficient (×1000)
Mar
Apr
May
Jun
Jul
Time


Moving Window Autocorrelation of BSE Subsample IX Returns
First-Order Autocorrelation
Apr
May
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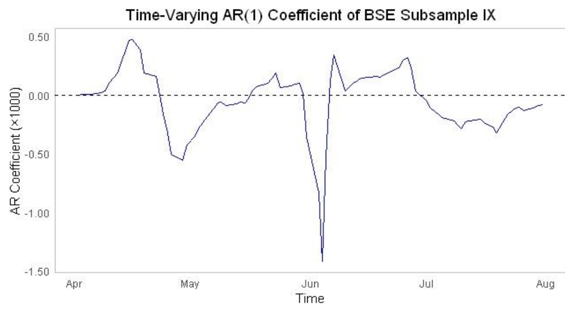
Time-Varying AR(1) Coefficient of BSE Subsample IX
AR Coefficient (×1000)
Apr
May
Jun
Jul
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Time

Chapter 5
Findings and Conclusion

This section focuses on the study's significant findings and the conclusions derived from them. It also discusses the policy implications, the contribution of the study, the limitations of the study, and the scope for further research.

5.1 Findings of the Study

The main findings of the study are summarised as follows.

5.1.1 Findings from Objective I

- The BSE(Sensex) full sample indicates that for shorter horizons, RWH is rejected, whereas for longer horizons it holds.
- For most subsamples of BSE(Sensex) and values of q, the RWH holds. Nevertheless, it appears that, for subsample VII —the period from 1st March till 31st June 2014 — the evidence of random walks disappears for shorter investment holding horizons, whereas for longer periods it still holds.
- With rejection of the random walk hypothesis for the Full sample and acceptance for the rest of the subsample period, except for subsample VII, the period from 1st March to 31st June 2014. 16th parliamentary elections, which also saw the regime change in India.
- Given that the data are characterised by changing volatility. Based on the value of Z*(q), we conclude that the results for the full sample of BSE(Sensex) are not as strong for longer investment horizons (q=8, q=16 days), but still reject the random walk hypothesis for q=2 and q=4.
- Pre- and post-financial crisis, COVID-19 indicate the same results for BSE(Sensex), indicating the level and the quality of activity in the Indian market remain the same.
- The predictability of returns remains for shorter horizons and vanishes for longer periods as the holding period increases.
- The full sample and Subsample V and Subsample VI of Sensex RWH are rejected, implying the market is weak-form inefficient.
- For BSE(Sensex), the Full sample of all test statistics for different holding periods is significant except for R_2 for holding periods of 8 and 16. Clearly, rank-based test

statistics are overwhelmingly accepted for q's ranging from 2 to 16 of the full sample, indicating that the random walk hypothesis does not hold.

- The individual and multiple variance ratio tests suggest the existence of time-varying predictability consistent with the Adaptive Market Hypothesis.
- Both Sample I and Sample II showed predictability in returns in the second and last months of the parliamentary election, suggesting a close relationship between the 10^{th} and 11^{th} parliamentary elections. Sample III and Sample IV return predictions were possible in the third month, suggesting inefficiency and a close relationship between the 12th and 13th parliamentary elections.
- The results of both the Generalised Spectral and Dominguez-Lobato tests confirm that market returns are evolving.

5.1.2 Findings from Objective II

- The remainder component shows irregular fluctuations, suggesting that other factors beyond seasonal patterns influence stock market behaviour. For instance, events such as the Asian Financial Crisis of 1997, the Dot-com bubble of 2000, the Global Financial Crisis of 2008, and the COVID-19 pandemic of 2020 may contribute to these high-frequency fluctuations.
- For both indices, h(q) is a decreasing function, indicating multifractality in the time fluctuations of the remaining component.
- The range of the Generalised Hurst exponent, Δh, is the same for the BSE Sensex and NSE Nifty market indices (0.24). Indicating the same degree of multifractality. This reflects the same level of efficiency.
- The Information efficiency of the Indian stock market is less capable of thoroughly and quickly reflecting all available information in asset prices.

5.1.3 Findings from Objective III

- In 1995, the estimated coefficient reached its highest level during the entire sample period. Thus, we assume that the Indian stock market was relatively inefficient during this period.
- The estimated coefficient remains constant from 2000 to 2015. After 2015, the market began to decline, reaching a negative point during the COVID-19 pandemic.

- For the Indian stock market, the period after 2015 indicates excessive market overreaction, implying that price movements are not only predictable but also disproportionately reverse, which is a sign of speculative behaviour and herding in the market.
- LPG policy (Liberalisation, Privatisation and Globalisation), also known as the New Economic Policy, was introduced in India on July 24, 1991. These could be the reasons for the market's momentum for the period from April 1st 1991, to 31 July 1991, suggesting inefficiency.
- Subsample VII witnessed a sharp shift towards efficiency; it was a period marked by another regime change.
- Subsample VIII - March 1 to June 1, 2019 – 17th Parliamentary Election. The market exhibited irrational behaviour towards the end of the election phase.
- Subsample IX: 1st March 2024 to June 30, 2024. The results were unexpected, as they resulted in the ruling party and its coalition losing a majority in the lower house. The market experienced a sharp decline, indicating that overreaction and herding behaviour occurred once the result was announced.

5.2 Conclusion of the Study

First, we examine the time-varying return predictability of the BSE Sensex, a primary Indian stock market index, using daily data for the 1989-2024 period and various sub-periods, classified by parliamentary elections. We aim to determine whether sufficient return gains can be achieved by exploiting the period of political uncertainty. We implement various variance-ratio tests to evaluate whether the two major indices across different periods of parliamentary elections follow a random walk. The tests implemented are the Lo-MacKinlay Variance Ratio Test, the Chow-Denning Multiple Variance Ratio Test, and the Wright (2000) Rank and Sign Test. While previous studies in the Indian context have reported mixed (Jain et al., 2013; Parthsarathy, 2016), the weak-form efficient (Dsouza & Mallikarjunappa, 2015; Poshakwale, 2002) rejects the weak-form efficient. Our analysis reveals that the market is not weak-form efficient but inefficient. The full sample rejects the random walk hypothesis, whereas the various period of parliamentary elections tends to be random. However, the period leading up to the 16th parliamentary election demonstrated predictability, which also saw a regime change. These have also not been reflected in past when such regime change has happened on a smaller scale. It is quite possible that information spread does not have any impact on the 16th parliamentary election, as social media has spread more widely than in the past. Before and after the 2008 financial crisis, and after the COVID-19 pandemic, the full sample and subsample tend to show the same level of activity.

Secondly, we evaluate the evolving return predictability and the adaptive market hypothesis (AMH) of the Bombay Stock Exchange (BSE) Sensex index. We use the Dominguez-Lobato Consistent Test (DL) and Generalised Spectral Test (GS) on rolling 100-day window returns for the full sample and 10 days to study time-varying return predictability. There are a total of nine samples over four months, each representing parliamentary elections. The result indicates that market efficiency evolves, validating the adaptive market hypothesis (AMH) and suggesting that extra returns can be exploited by speculators and arbitrageurs through various strategies, even during the phase of parliamentary elections. Predictability was high during the 11th parliamentary election (Sample II), signifying high inefficiency. Recent parliamentary elections (16th and 17th) also suggest the presence of Inefficiency (Predictability), implying that easy access to information has little impact on the market.

Thirdly, we study the degree of market efficiency for the BSE Sensex and NSE Nifty over the long run. We apply seasonal and trend decomposition using LOESS before applying MF-DFA. We see that, for both indices, h(q) is a decreasing function, indicating multifractality in the time fluctuations of the remaining component. The range of the Generalised Hurst exponent, Δh, is the same for the BSE Sensex and NSE Nifty market indices (0.24). Indicating the same degree of multifractality. This reflects the same level of efficiency. Across various BSE subsamples, multifractality is greater, indicating inefficiencies. For all considered subsample periods, market efficiency did not exist; rather, inefficiency was noticed. The most significant degree of multifractality was identified in the BSE subsamples IV and IX (which indicate the lowest market efficiency).

The STL decomposition of Index returns reveals irregular fluctuations in the residual component, suggesting that factors beyond seasonal patterns influence stock market behaviour. For instance, events like the Asian Financial Crisis of 1997, the Dot-com bubble of 2000, the Global Financial Crisis of 2008, and COVID-19 of 2020 may contribute to these high-frequency fluctuations. The remainder component appears noisy; it is essential to note that this noise is not purely random. Instead, it likely stems from various macroeconomic factors influencing the stock market beyond seasonal cycles. The degree of market efficiency varies over time. It differs across the phases of parliamentary elections, validating the adaptive market hypothesis (AMH) and suggesting that extra returns can be exploited by speculators, portfolio managers, and individuals through various strategies.

Lastly, Variation in Index returns can be observed over both short and longer horizon periods. The degree of market inefficiency varies with time and differs across the phases of parliamentary elections, validating the adaptive market hypothesis (AMH). The variation in the degree of stock market inefficiency presents an opportunity for investors and portfolio managers to generate substantial overall returns by exploiting price discrepancies. However, it is also observed that informational asymmetry fades with time as it is fully reflected in stock prices. As a result, the level of inefficiency in the Indian Stock Market fluctuates across different periods, gradually shifting the market from efficient to inefficient.

5.3 Policy Implications of the Study

This study may serve as a guide for domestic and foreign investors in making long-term investment decisions during elections. Traders can exploit inefficiencies during the election period and make extraordinary gains. The study's findings on evolving characteristics of market efficiency may affect regulations and market growth. Policymakers and regulators are required to continuously monitor and introduce new measures to avoid problems during the parliamentary elections in the market.

5.4 Contribution of the Study

This study makes several significant contributions to the literature on the Adaptive Market Hypothesis. We are the first to study the Adaptive Market Hypothesis during the phases of parliamentary elections, examining the time-varying predictability of returns and their evolution in the Indian Stock Market. Secondly, the moving window approach uncovers changes in short-term linear dependence over time, offering a richer perspective on time-varying return predictability during the phases of parliamentary elections. Thirdly, we also examine the efficiency of various BSE Sensex subsamples over the long run. By applying seasonal and trend decomposition using LOESS, the deterministic components are removed from the return data series, thereby avoiding misinterpreting seasonality and trend as multifractal behaviour. While the BSE Sensex and NSE Nifty market indices indicate the same degree of multifractality. The highest degree of multifractality was observed in BSE subsamples IV and IX, indicating the lowest market efficiency. MFDFA also enables us to handle non-stationarity that traditional methodologies would not. Fourthly, by studying imperfections in the price-formation processes across various parliamentary elections, which reveal time-varying inefficiency, appropriate policies can be devised by policymakers and regulators. The variation in the degree of stock market inefficiency presents an opportunity for investors and portfolio managers to generate substantial overall returns by exploiting price discrepancies. This research bridges the gap between Time-varying predictability, information efficiency and inefficiency across India during the phases of parliamentary elections.

5.5 Limitations of the Study

The Hurst exponent can be dynamically computed using a sliding-window method, which could provide important insight into its evolution during the parliamentary election. There may be other specific events that influenced the short period of inefficiency, which are not examined in this study. The findings of this study cannot be generalised across different periods or markets and are valid only for the study period.

5.6 Scope for Further Research

This study provides a unique new dimension for further research. First, to investigate the effect of news and sentiments attached to the news on stock prices during the phases of parliamentary elections, which can provide a deeper understanding of the information dynamics and how it is incorporated in the stock prices. Secondly, future studies can identify other periods of inefficiency and apply tests, techniques and approaches with detailed historical perspectives. There is also scope to study the global stock market during various elections at the country level.

Research Paper Publication

1) Published a research paper titled "Does the random walk hypothesis hold for Indian stock markets during parliamentary elections? In the Asian Economic and Financial Review journal. Scopus Index(Q2). https://doi.org/10.55493/5002.v13i12.4889 Link to Webpage: - https://archive.aessweb.com/index.php/5002/article/view/4889.

Research Paper Presentations

1) Presented a research paper at Sadguru Gadgae Maharaj College, Karad, Maharashtra, on "Predictability of Sectoral Returns of Emerging Sector" at the International Conference on "Recent Trends and Challenges in Commerce and Management" on 6th May 2022.
2) Presented a research paper titled "Adaptive Market Hypothesis and Evolving Stock Return Predictability of Indian Stock Markets" at SJU 1st International Conference on Multidisciplinary Research & Innovation (ICMRI-2023) organised by Internal Quality Assurance Cell (IQAC), St. Joseph University, Chumoukedima, Nagaland on 09th & 10th November, 2023.
3) Presented a research paper titled "A Study on Adaptive Market Hypothesis of Indian Stock Market Indices BSE (Sensex) and NSE (Nifty) by use of Multifractal Detrended Fluctuation Analysis (MF-DFA), at Sri. Padmavati Mahila Visvavidyalayam, Tirupati. SJU two-day International Conference on Emerging Trends in Business & Entrepreneurship in the Digital World, held on 9th and 10th March 2024.

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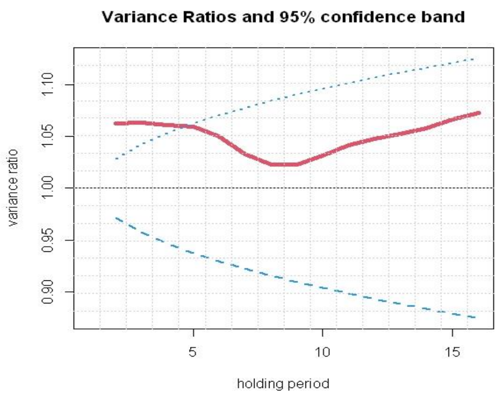
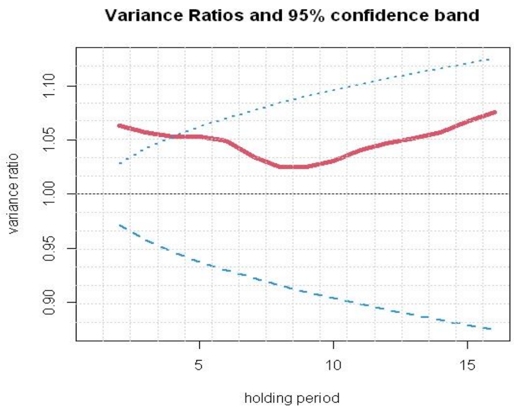
Annexure

Figure A1. Variance Ratio Plot of BSE(Sensex) and NSE(Nifty) Full Sample at 95% Confidence Interval.

(a) BSE (Sensex)



(b) NSE (Nifty)



a1. https://www.5paisa.com/blog/best-social-media-stocks

** Data and code are available on GitHub. Link -https://github.com/sang4311/ito-paper