A STUDY ON INDIAN STOCK MARKET EFFICIENCY: A MULTI-DIMENSIONAL APPROACH

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By

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DECLARATION

I hereby declare that all the work presented in the thesis entitled **"A Study on Indian Stock Market Efficiency: A Multi-Dimensional Approach"** in fulfillment of the requirement for the award of the degree of Doctor of Philosophy in University School of Management and Entrepreneurship, Delhi Technological University, Delhi is an authentic record of my work carried out under the guidance of **Dr. Deepti Aggrawal,** Assistant Professor, University School of Management and Entrepreneurship, Delhi Technological University, Delhi **and Dr. Jagvinder Singh,** Assistant Professor, Department of Operational Research, University of Delhi.

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CERTIFICATE

This is to certify that the work embodied in the thesis entitled **"A Study on Indian Stock Market Efficiency: A Multi-Dimensional Approach"** is done by **Reema Monga** as a research scholar in University School of Management and Entrepreneurship, Delhi Technological University is the authentic work carried out by her under our supervision.

This work is based on original research, and the matter embodied in this progress report has not been submitted earlier for the award of any degree or diploma to the best of my knowledge and belief.

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LIST OF ABBREVIATIONS

AMH	:	Adaptive Market Hypothesis
AVR	:	Automatic Variance test
BSE	:	Bombay Stock Exchange
CDF	:	Cumulative Distribution Function
CET	**:**	Coefficient of Elasticity of Trading
CPQS	:	Closing Percent Quoted Spread
EMH	:	Efficient Market Hypothesis
EW	:	Equal Weighting
FW	:	Factor Weighting
HML	:	High Minus Low
INV	:	Investment
LVOL	:	Low Volatility
MEC	:	Market Efficiency Coefficient
MOM	:	Momentum
MPT	:	Modern Portfolio Theory
NSE	:	National Stock Exchange
PROF	:	Profitability
RP	:	Risk Parity
RQS	:	Relative Quoted Spread
RWH	:	Random Walk Hypothesis
S-Factor Scores	:	Standardized Factor-scores
SMB	**:**	Small Minus Big
ST	:	Share Turnover
VR TEST	:	Variance Ratio Test

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Chapter 1
Introduction

CHAPTER 1
INTRODUCTION

1.1 Background

Stock markets are pivotal in economic development, especially in developing economies. Claessens et al. (1995) observed that stock markets are tremendously efficient in allocating capital, improving overall economic efficiency. Put another way, the stock market makes capital allocation and economic growth possible, which is an essential part of contemporary economies. They provide asset diversification, lowering capital costs and encouraging more investment and growth. A vital factor in the way equities markets operate is the concept of market efficiency. In other words, stock market efficiency is a vital concept in finance theory that influences investor behavior and regulatory measures. When stock prices accurately reflect all available information, it becomes more challenging for investors to generate abnormal returns regularly using various investment strategies. Antoniou et al. (1997) observed that the effectiveness of a stock exchange is crucial since it allows prices to incorporate information completely. Saving and investing are encouraged since it gives investors the confidence to trade in the stock market. It also encourages investors to engage in other regional stock markets besides encouraging market growth. A stock market that lacks efficiency may deter investors from trading there, which will impede the growth of the economy.

In neoclassical finance, the notion of market efficiency is one of the key ideas that have been extensively researched. Fama (1965, 1970) proposed the theory of the EMH (Efficient Market Hypothesis) and the phenomenon of market efficiency.

According to the EMH or Random Walk Theory (Kendall, 1953), the firm's current stock price appropriately reflects all information that is currently available, and there is no way to increase profits by exploiting this information. A critical factor in determining market efficiency (information efficiency) is whether or not prices fairly reflect all available information. In essence, markets are efficient if prices accurately represent all available information (Fama, 1970).

According to Eakins and Mishkin (2012), two pillars form the foundation of an efficient market: 1) Stock prices in efficient markets already take into account all available information; 2) investors are unable to obtain an excess return in efficient markets. Stock markets are operationally efficient when they possess liquidity, the market condition is orderly (i.e., there is continuity of trading and no market manipulation), and there is a well-functioning market system.

EMH has three forms of market efficiency that characterize how much information is represented in stock prices; one is the weak form of market efficiency. According to the weak-form efficiency, stock prices already take into account all historical trade data. Stated differently, it implies that all of the historical information about the market, including price and volume data, is entirely and instantly reflected in the prices of current stocks. The second form of the market efficiency is classified as the semi-strong form of EMH. This form asserts that stock prices already take into account all information that is known to the public. Put differently, when new information becomes accessible to the public, stock prices react to it promptly and accurately. In this form of EMH, stock prices reflect all information that is readily available to the public, including historical data, economic indicators, financial statements, and any other pertinent information. As a result, investors will not always get higher returns from trading on information that is readily available to the public. Within the framework of the EMH, the next type is the strong form of market efficiency. It assumes that stock prices fully and instantly reflect all information, whether it is public or private. Put differently, this includes insider information that is exclusively known to a small number of people as well as information that is accessible to the broader public. Hence, no investor or group can profitably trade on any kind of information in a market that follows a strong form of efficiency.

1.2 Introduction to the Problem

The idea of Efficient Market Hypothesis has been one of the most contentious subjects in the financial literature. The concept of informationally efficient markets was first accepted, but some flaws in the EMH made it challenging to apply in real-world scenarios. EMH has undergone several tests to ascertain its viability in the financial markets, even if a consensus has never been reached. This has caused a rift among academics, with some endorsing behavioral biases that may impact the financial markets and others standing up for the EMH. Lo (2004) put forth a new paradigm, the Adaptive Markets Hypothesis (AMH), which takes an evolutionary view of human behaviour that affects the informational efficiency of markets. Lo (2004), in particular, suggests a new AMH concept that makes it possible for behavioral finance and the EMH to coexist in a logically consistent manner. Interestingly, the concepts behind the AMH were inspired by a wide range of literature, including works on complex systems, behavioral ecology, evolutionary psychology, evolutionary biology, and bounded rationality in economics.

According to AMH, the degree of market informational efficiency is determined by the capacity of market players to adjust to evolving market circumstances. In other words, Lo (2004) used the AMH to present a new viewpoint on the changing nature of the market. In a logically consistent manner, the AMH establishes the presence of market efficiency and inefficiencies; in contrast to EMH, market efficiency in AMH changes with time. Lo (2004) examined the time-varying aspect of efficiency and found that AMH is a more reliable method than EMH because it acknowledges that human error can cause arbitrage opportunities, which disappear once they have been taken advantage of. In other words, arbitrage possibilities occasionally arise and fade as investors take advantage of them, which in turn creates new opportunities that emerge from shifts in the market dynamics. Lastly, the notion of cyclical profitability in investing approaches implies that a specific strategy will work well in one context and poorly in another.

An outcome of AMH is that market efficiency is “not an all-or-nothing condition” and fluctuates over time. Stated differently, the degree of market efficiency is not constant because of the dynamic risk-reward relationship that is dependent on past market prices and participant preferences. Thus, convergence to market efficiency is neither certain nor likely to happen because there are always fresh opportunities for profit to be made. In a nutshell, the theory of AMH has received more attention in the most recent academic research. The results seem very promising; with several studies finding strong evidence of the adaptive behavior of stock returns (Urquhart & McGroarty, 2014, 2016).

For the stock market to operate smoothly, liquidity is a necessary feature of the market. Put otherwise, market liquidity is critical to the equities market since it ensures both the market's stability and the tradability of assets. On the other side, a lack of liquidity causes the market to become unstable. According to Amihud et al. (2006), market liquidity is the state in which willing buyers and sellers agree to exchange a specific amount of assets at the stipulated price without any delay. Furthermore, Brennan et al. (2012) defined liquidity as the market's capacity to quickly and efficiently absorb a large number of securities at a lower execution cost without significantly affecting its prices. Liquidity in the equity market is crucial for the economy as well. Ellington (2018) noted that lower liquidity levels have a detrimental effect on economic growth during a crisis. Additionally, Nneji (2015) pointed out that market liquidity demonstrates the market's resilience to shocks and financial crises. Studies by Naes et al. (2011); Smimou, (2014) and Apergis et al. (2015) found that liquidity was crucial in determining how the economy would perform in the future.

Liquidity in the stock market has been measured using a number of different metrics such as depth (measured by volume or quantity), immediacy (determined by time or speed), transaction costs (measured by bid-ask spread or transaction cost), and breadth (determined by price impact). It is noted that different authors have conceptualized market liquidity differently in the literature (Sarr & Lybek, 2002; Bhattacharya et al., 2019; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Naik et al., 2020; Naik & Reddy, 2021a). As a result, measuring market liquidity has proven to be challenging for earlier research.

Stock market efficiency typically corresponds with its liquidity. (Banerjee & Ghosh, 2004) noted that with regard to the equities markets, the idea of liquidity includes the potential for low-cost execution of substantial transactions. A lack of liquidity in the stock market allows one to predict stock prices rather accurately and benefit excessively, demonstrating inefficiency in the market. Furthermore, liquidity is required to manage risks in an efficient manner. Investors may rapidly and affordably modify their portfolios in an efficient market with strong liquidity, which helps them manage risk more effectively. Put another way, effective trading positions improve market efficiency by enabling investors to react quickly to changing market situations.

High liquidity is associated with heightened investor confidence in the efficiency and fairness of the market. Investors are more likely to believe that prices accurately reflect available information in a market that operates with liquidity and efficiency. A significant factor in liquidity is the constant quotation of ask and bid prices by market makers. Various studies noted that market makers maintain liquidity in an efficient market by encouraging trade and minimizing bid-ask spreads. Their presence guarantees that stocks can be purchased or sold without significantly impacting price, therefore increasing market efficiency.

In light of the fluctuations in the traditional index and the impact of inefficient stock markets, investors have started looking for transparent and rule-based indices that apply non-market-cap weighting schemes. These alternative weighted portfolios are termed by the expressions "advanced beta," "smart beta," "alternative beta," "factor investing," and "alternative risk premium and more"(Kudoh et al., 2015; Blitz, 2016). These strategies aim to alleviate the inherent frailty of traditional market indices, i.e., "overweighting overpriced stocks and underweighting underpriced stocks." In other words, this relatively new approach to equity investing is prompted to address these shortcomings (heavy concentration and unfavorable factor exposures) of conventional market indices. Thus, alternative equity indices aim to gain advantages from rewarded risk-premia factors while diversifying unrewarded risks using broadened weighting schemes.

1.3 Scope of the Study

The focus of researchers, market players, and investors alike is increasingly shifting to emerging stock markets. This is not surprising considering the remarkable growth these markets have seen. Apart from their tremendous growth, stocks in emerging countries do not exhibit much correlation with those in developed countries, and systematic patterns in the returns make them more predictable.

Due to their extremely high economic growth rates and impressive equity returns, Asian emerging markets have become the world's most imperative emerging market region (McKinsey and Company, 2018; OECD, 2019). With a market capitalization of $3.46 trillion, the Indian stock market is the fifth-largest stock market in the world (Bloomberg, 2023). Because of its growth potential, size, stable macroeconomic environment, foreign interest, and market capitalization, it is a desirable emerging market for FIIs and other international portfolio investors. About 29% of Indian shares were owned by foreign portfolio investors (FPIs) in 2019. Intriguingly, the Indian stock market saw the most significant FII inflows for the year 2020 among emerging markets. Given the high growth rates and opportunities, India remains a popular investment location with sizable foreign portfolio investment. For instance, in 2020- 2021, the total net investment of these FPIs reached a record high of approximately $555 billion. With a PPP-adjusted GDP of $10.21 trillion, it is also the third-largest economy in the world (World Bank, 2021).

1.4 Significance and Contribution of the Study

We contribute to the literature in the following ways. First, our study investigates the weak-form market efficiency in the Indian market. Given its potential for growth, history of structural and economic downturns, and institutional heterogeneity, the Indian stock market presents an intriguing opportunity to examine the two approaches of efficiency, i.e., absolute and evolving market efficiency. Interestingly, this work offers a thorough analysis of the weak-form market efficiency through the application of both linear and nonlinear statistical tests. Moreover, subsample analysis, which may distort the results, was substituted with rolling window analysis, which gradually describes how predictability changes over time. In other words, the main drawback of subsample analysis is the bias in subsample selection, which might affect the findings.

Second, a number of studies highlight the drawbacks of relying solely on a single metric or proxy to evaluate liquidity (Sarr & Lybek, 2002; Bhattacharya et al., 2019; Diaz & Escribano, 2020; Naik et al., 2020; Le & Gregoriou, 2020; Naik & Reddy, 2021a)., i.e., there is no universal agreement on the best measure to use. Consequently, we employed the multifaceted notion of liquidity, encompassing the five distinct dimensions: depth, tightness, breadth, immediacy, and resiliency. Further, there is a dearth of research on the linkage between efficiency and market liquidity. Thus, the EMH is tested in this study on the returns of several stocks that have been sorted for market liquidity.

Third, there is substantial evidence regarding the existence of anomalies. However, the literature is mainly limited to the U.S. and other mature markets. In a growing market like India, these anomaly-based investing strategies may or may not be effective. Therefore, given the lack of such empirical evidence, the current study focuses on the construction, execution, and performance of the anomalies-based investment in the scarcely researched emerging Indian equity market.

Lastly, this study is one of the earliest attempts to examine alternative equity indexing strategies by implementing various optimization-based strategies (Efficient Minimum variance, Diversified Risk-weighted, Maximum deconcentration, Maximum decorrelation, Efficient maximum Sharpe ratio, and Diversified Multi-Strategy). Also, earlier studies have concentrated exclusively on long-term results and do not account for the time-varying existence of these strategies. Therefore, this research uses sub-sample analysis to study the time-varying nature of various optimized strategies and account for different economic circumstances in the Indian context.

Chapter 2

Literature Review and Theoretical Framework

CHAPTER 2
LITERATURE REVIEW AND THEORETICAL FRAMEWORK

INTRODUCTION

2.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis, a foundational theory of finance, maintains that financial markets are efficient and that asset prices fairly reflect all available information. According to this theory, it is impossible to surpass the market and attain remarkable profits as all tradable securities and assets instantaneously reflect recently revealed information. Put another way, the randomness of stock returns is the central tenet of the EMH. Second, investors are unable to profit excessively in an efficient market. The main idea behind the EMH is that at any given time, financial market prices consider all available information and reflect the collective beliefs and expectations of all market participants. In other words, asset prices always accurately reflect their intrinsic value based on the information available, and it is difficult to continually outperform the market by using historical price movements or information that is readily available to the public.

2.1.1 Forms of the Efficient Market Hypothesis

Market efficiency is divided into three groups: weak, semi-strong, and strong forms of efficiency, dependent on the type of the information. According to the weak form of EMH, the current stock prices already take into account all historical trade data, including prices and volumes. Stated differently, this kind of efficiency implies that it is not possible to predict future stock prices from past data. Over the years, the weak form of market efficiency has been examined by previous studies (Kim & Shamsuddin, 2008; Sharma & Mahnedru, 2009; Khan et al., 2011; Harper & Jin, 2012; Smith, 2012, Nalina & Suraj, 2013; Urquhart and Hudson, 2013; Sensoy 2013; Jain & Jain, 2013; Gupta & Gedam, 2014; Tiwari & Kyophilavong, 2014; Kumar & Kumar, 2015; Mishra et al., 2015; Hiremath & Narayan, 2016; Vidya, 2018; Malafeyev et al., 2019; Shahid et al., 2019; Vasileiou, 2021; and Munir et al., 2022). As a result, past research investigations suggested substantial evidence for weak forms of efficiency, while others argued against them.

Under the semi-strong form of market efficiency, stock prices represent all information available to the public, including information from the past and information that has been made public. This form assumes that stock prices already take into account all information that is publicly available, including news, economic indicators, financial statements, and earnings announcements. Put differently, investors find it challenging to regularly take advantage of the disclosure of new information to earn abnormal returns because the market reacts immediately to new information. As a result, an investor should not have an advantage in projecting future stock prices when utilizing technical or fundamental analysis.

In the strong form of EMH, stock prices reflect all information that is accessible, including information open to the public, as well as insider and confidential information. Particularly, this version of the EMH implies that stock prices fairly represent information that is only known by a small number of people or insiders. Stated differently, according to this form of efficiency, all available public and private information is already included in the current stock price. So, even with insider information, no investor, retail or institutional, should be able to generate excess returns continuously.

When it comes to market efficiency, there are two schools of thought. The first contends that future returns are unpredictable and markets are efficient (Fama, 1970). The second group, however, argues that the empirical evidence of “anomalies” makes the EMH inconsistent. According to the weak-form market efficiency theory, past data is useless for predicting future returns since all the historical information is expected to be included in the current returns. The literature has several contradicting findings regarding the weak form of EMH in various global marketplaces. Predominantly, some studies validate the presence of weak form efficiency, while others refute it.

Abeysekera (2001) examined the Random Walk Hypothesis (RWH) for the Colombo Stock Exchange (CSE) in Sri Lanka using daily, weekly, and monthly prices. Throughout the sample period of 1991 to 1996, the study used the unit root test, runs test, and autocorrelation test. The results demonstrate a rejection of the Random Walk (RW) and lead to the conclusion that the market is inefficient. Mobarek and Keasey (2002) examined the weak-form efficiency concerning the Dhaka stock market. According to their findings, the stock market is not weakly efficient. Smith and Ryoo (2003) used weekly data and variance ratio tests to study the RWH in five European emerging markets (Turkey, Poland, Greece, Portugal, and Hungary). According to the research, the Istanbul stock market was the only equity market that adheres to the theory of Random Walk. This is explained by the fact that the Istanbul equity market is bigger and comparatively more liquid than the other four equity markets. Using the autocorrelation and unit root tests, Akinkugbe (2005) investigated the weak-form efficiency in the Botswana stock market. Throughout the sample period of 1989 to 2003, the study found indications of random walk behavior, i.e., exhibiting weak-form efficiency.

Worthington and Higgs (2006) investigated the weak-form efficiency of five developed and ten emerging Asian markets using serial correlation coefficients and run tests. The results showed that the emerging markets (China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Sri Lanka, Taiwan, and Thailand) were inefficient and showed no signs of random walk behavior. Hoque et al. (2007) examined the weak-form of EMH using Lo-MacKinlay and Chow-Denning tests along with two variance ratio tests: Wright's rank and sign and Whang-Kim subsampling tests. Particularly, the study covered eight Asian equity markets throughout the pre-and post-Asian crisis periods and found no significant impact on market efficiency. In parallel, Kim and Shamsuddin (2008) tested the weak-form efficiency using a variety of variance ratio tests (wild bootstrap and signs test). Nonetheless, the analysis found that the Asian financial crisis had no significant impact on efficiency. Mishra (2011) tested the weak form efficiency of selected emerging and developed capital markets (India, China, Brazil, South Korea, Russia, Germany, the U.S., and the U.K.) over the sample period spanning from January 2007 to December 2010. The study concluded that these equity markets are not weak-form efficient. Nisar & Hanif (2012) studied the weak form EMH for South East Asia markets- India, Pakistan, Bangladesh, and Sri Lanka Stock Exchanges. According to the research, these stock markets are inefficient because they do not adhere to the random walk model. Das (2014) used the Variance Ratio test and the Augmented

Dickey-Fuller (ADF) unit root test to investigate the RWH in the Indian equities market. The author covered the period of global financial crisis, and looked at market efficiency in three phases: the pre-crisis, crisis, and post-crisis. The findings of the empirical research indicate that stock returns are inefficient throughout the periods of pre-crisis and crisis; however, they are particularly inefficient during the crisis and are likely to be efficient during the post-crisis phase.

Azad et al. (2014) looked into the weak-form market efficiency in emerging South Asian markets, such as the stock exchanges in Bangladesh, India, and Pakistan. The study found the existence of weak-form inefficiency in these South Asian markets. In parallel, Tiwari and Kyophilavong (2014) investigated the market efficiency of the BRICS stock indexes. In particular, the analysis discovered weak-form inefficiency in these markets, with the exception of the Russian stock index.

Obayagbona and Igbinosa (2015) demonstrated that the Nigerian market exhibits evidence of weak form inefficiency by displaying dependency on the series of returns and, thus, does not adhere to the concept of random walk. On the contrary, Kelikume (2016) examined the Nigerian stock market between 1985 and 2015, demonstrating that it exhibits random walk behavior and validating efficiency.

Ozkan (2021) used an automatic portmanteau test and wild bootstrap automated variance ratio test and investigated the market efficiency for the six developed stock markets: Germany, the United States, the United Kingdom, France, Italy, and Spain. The research found that the COVID-19 pandemic increased market inefficiencies, suggesting a greater probability of predictability and anomalous returns. Baig et al. (2021) concluded that the liquidity and stability of the U.S. equity market are negatively impacted by the lockout connected to COVID-19. In parallel to this, Vasileiou (2021) investigated the efficiency of the U.S. stock market and found that the market exhibited inefficiency during the pandemic.

There are several studies conducted in the Indian context, including those by Poshakwale (1996), Srinivasan (2010); Gupta and Siddiqui (2010), Khan et al. (2011), Harper and Jin (2012), Kumar & Kumar (2015), Kumar & Jawa (2017), Patel et al. (2018), Malafeyev et al., (2019), and Elangovan et al., 2021) have challenged the validity of the EMH and found that the Indian equity markets were weak-form inefficient.

Poshakwale (1996) applied the Serial Correlation Coefficient test, Runs test, and Kolmogorov Smirnov (K.S.) on daily prices of the Bombay Stock Exchange Index from January 1987 to October 1994. The study rejected the market efficiency after it was found that the results of the tests (the run and serial correlation coefficient tests) did not follow the random walk model. Using weekly and daily returns, Pant and Bishnoi (2001) looked into the Random Walk Hypothesis in the Indian equity market. According to the results of the variance ratio, autocorrelation, and unit root test, the market was inefficient between 1996 and 2000. Gupta and Siddiqui (2010) utilized the autocorrelation test, runs test, and Kolmogorov–Smirnov test to investigate the weak form of market efficiency over the years 2000–2008. The results show that the Indian stock market defies the random walk theory, indicating that there is no weak form of market efficiency.

Khan et al. (2011) used the BSE and NSE index daily closing values from April 1, 2000, to March 31, 2010. The study employed the nonparametric runs test, which revealed that the Indian equity market is neither weak form efficient nor fits the random walk model. Harper and Jin (2012) studied the weak-form market efficiency of the Indian equity market from July 1997 to December 2011. The study used runs and auto-correlation tests and concluded that the Indian stock market is inefficient. Mishra et al. (2015) used 19 years of monthly data from six NSE indices to study the RWH of the Indian stock market. The results suggested that the Indian market is not conducive to RWH. In parallel to this, Kumar and Kumar (2015) found that investors may be able to obtain abnormal returns by taking advantage of market inefficiencies and that stock prices in India do not accurately reflect all the available information.

Using the runs test, Patel et al. (2018) investigated the market efficiency of the Indian stock market from April 2015 to March 2018. Their research indicates that market players can outperform since the market is not efficient. The latest study by Jain et al. (2020) was conducted on the Indian stock market efficiency based on BSE and NSE from April 2010 to March 2019. The results concluded that the Indian equity market does not adhere to the theory of weak-form EMH and, therefore, can be outperformed. Particularly, the findings indicate that investors can generate anomalous returns and that the Indian equity market does not follow a random walk. However, studies by Sharma and Mahnedru (2009), Nalina and Suraj (2013), Jain & Jain (2013), Gupta and Gedam (2014), Mishra et al. (2015), and Vidya (2018) found that changes in the stock market prices are random, and thus, confirmed that the Indian equity market is weak-form efficient.

Previous studies and research on weak-form of EMH utilized models that differed from conventional models to advance. However, no definitive result has been reached on the efficiency or inefficiency of the market, which resulted in contradictory results

(Borges, 2010; Gupta & Yang, 2011, Al-khazali et al., 2016; Parulekar, 2017, Al-khazali & Mirzaei, 2017; Kapoor, 2017). The weak form of efficiency in the Indian stock market was suggested by Jain & Jain (2013), Nalina & Suraj (2013), and Mishra et al. (2015). Conversely, the Indian market was shown to be weak-form inefficient by Poshakwale (1996), Gupta and Siddiqui (2010), Srinivasan (2010), Khan et al. (2011), Malafeyev et al., (2019) and Bhatia (2022). In particular, investors are becoming more focused on comprehending the efficiency of the stock market in order to capitalize on investment opportunities. Thus, further research is needed to add to the current discourse on efficient market theory.

2.2 Adaptive Market Hypothesis (AMH)

Most previous research on market efficiency has employed the conventional methodology of evaluating weak-form efficiency, which has two fundamental limitations. First, as per the study by Campbell et al. (1998), this approach considers that a market is efficient over a whole period as an all-or-nothing condition and ignores the notion of evolving efficiency (i.e., efficiency to change over the period). Second, the conventional method makes the assumption that market efficiency will remain constant for a given amount of time. However, this is very unlikely as many factors will result in the degree of market efficiency varying over time (Lim & Brooks, 2011). The AMH proposed by Lo (2004) enables market efficiency and inefficiencies to coexist in an intellectually consistent manner. According to the theory of AMH, market efficiency changes over time instead of adhering to the common notion of “all-or-nothing efficiency”.

In the most recent academic literature, the AMH has drawn more and more attention, where there is compelling evidence of the adaptive behavior of stock returns (Ito &

Sugiyama, 2009; Kim et al., 2011; Alvarez-Ramirez et al., 2012; Dyakova & Smith, 2013; Hiremath & Kumari, 2014; Tuyon & Ahmad, 2016; Hiremath & Narayan, 2016; Charfeddine & Khediri, 2016; Numapau Gyamfi, 2018; Ndubuisi & Okere, 2018; Xiong et al., 2019; Okorie & Lin, 2021). Lo (2004) introduced the concept of AMH to bridge the gap between EMH and Behavioural Finance, which explains that efficiency and anomalies can alternate cyclically due to changes in investment environments. The theory of AMH states that financial markets are not always perfectly efficient but are instead influenced by human behavior and learning. It argues that market participants continuously adapt their strategies in response to changing market circumstances, leading to periods of market efficiency and inefficiency.

Lo (2004) creates a novel framework of AMH which is based on the well-known concepts of evolution, competition, adaptation, and natural selection. AMH brings behavioral finance principles back together with the EMH theory, i.e., balances financial interactions with market efficiency. The theory of AMH claims that the leading causes of the ups and downs of investment performance cycles are shifts in market conditions, including industry competition, investor flexibility, and the number of profit opportunities (Lo, 2005, 2012). Particularly, market efficiency is likely to exhibit cyclical patterns that emphasize the indication of AMH, especially in view of the rapid changes occurring in financial technologies, macroeconomic institutions, market laws, and regulations, among other areas (Kim et al., 2011).

In contrast to the EMH, the AMH contends that arbitrage possibilities occasionally appear because of market trends, crashes, bubbles, and panics. Market timing is a critical element in maximizing profit opportunities. The AMH suggests that financial markets are not entirely efficient, as assumed by the EMH. However, instead, they can adapt and evolve due to the changing behavior of market participants and the interplay of their trading strategies. Similarly, the profitability of investment strategies may also temporarily increase or decrease due to market conditions (Lo, 2004).

Market efficiency may be impacted by a wide range of factors (Lim and Brooks, 2011). These include financial crises, market uncertainty, financial liberalization, the implementation of automated trading systems, technology advancements, the easing of price limitations, and modifications to regulatory frameworks. Most past research examining the EMH in stock markets has concentrated on a specific market over a limited period of time. This conventional approach concludes that market efficiency is static, i.e., the stock market is either weak-form efficient or not during the entire time. However, there are strong arguments in favor of the theory that market efficiency is not static but rather varies over time (Lo, 2004; Abdmoulah, 2010; Kim et al., 2011; Dyakova & Smith, 2013; Hiremath & Narayan 2016; Lekhal & Oubani, 2020). After analyzing the monthly returns of the S&P Composite Index over a five-year rolling timeframe from 1871 to 2003, Lo (2004) came to the conclusion that market efficiency varied cyclically throughout the time. This theory states that market players adapt to changing market conditions and that return predictability varies in response to changes in business environments and potential profits (Lo, 2004, 2005). In a nutshell, the time-varying character of market efficiency is explained by the theory of AMH.

The concept of AMH is examined in the literature using two methods. The "time-varying model" technique is the first to investigate market efficiency (Ito et al., 2014; 2016). These investigations have led to the conclusion that market efficiency is time-varying, i.e., fluctuating with time. The second method (Lo, 2004; Kim et al., 2011; Dyakova & Smith, 2013; Lim et al., 2013) investigates market efficiency through statistical testing based on the "moving window" method. The studies related to AMH are both for developed (Lo, 2004; Ito & Sugiyama, 2009); Kim, et al., 2011; Alvarez-Ramirez et al., 2012; Butler & Kazakov, 2012; Urquhart & Hudson, 2013; Lim et al., 2013; Urquhart et al., 2015; Urquhart & McGroaty, 2016; Noda, 2016; Boya, 2019) and emerging stock markets (Lim, 2007; Todeo et al., 2009; Abdmoulah, 2010; Smith, 2012; Popovic et al., 2013; Dyakova and Smith, 2013; Hiremath & Kumari, 2014; Tuyon & Ahmad, 2016; Hiremath & Narayan, 2016; Charfeddine & Khediri, 2016; Numapau Gyamfi, 2018; Ndubuisi & Okere, 2018; Xiong et al., 2019; Shahid et al., 2019; Phan Tran Trung & Pham Quang, 2019; Lekhal & Oubani, 2020; Kılıç, 2020; Munir et al., 2022).

Lim (2007) studied the daily returns for two developed (USA and Japan) and eleven developing (Argentina, India, Chile, Indonesia, Taiwan, Brazil, Malaysia, South Korea, Thailand, Mexico, and Philippines) countries using a rolling sample portmanteau bi-correlation test. The research employed a rolling window of 50 observations and found that market efficiency follows an AMH-consistent pattern of fluctuations over time. Ito and Sugiyama (2009) used the rolling monthly returns of the S&P 500 index to determine first-order auto-correlations. The research spanned January 1955 to February 2006, and discovered that market efficiency varies with time, reaching its highest points of inefficiency in the late 1980s and efficiency in the early 2000s. Gupta and Yang (2011) conducted an analysis of market efficiency for the Indian stock market between 1997 and 2011. The analysis concluded that market efficiency occurred inconsistently or that there were periods of efficiency and inefficiency.

Using a rolling window variance test ratio, Smith (2012) studied the daily returns of fifteen developing and three developed nations in Europe from February 2000 to December 2009. According to the findings, Estonia, Malta, and Ukraine are the least efficient markets, while the U.K, Turkey, Poland, and Hungary are the most efficient. Urquhart and Hudson (2013) used the auto-correlations, runs, and VAR tests to evaluate market efficiency for the three developed nations: the U.S., the U.K., and Japan. The results indicated the presence of an adaptive market, supporting the claim that AMH offered a more accurate depiction of the behavior of equity returns than the theory of EMH. Niemczak and Smith (2013) tracked the evolving market efficiency for the eleven Middle-East financial markets and found that most of these markets followed AMH, i.e., switched between periods of efficiency and inefficiency. Sensoy (2013) applied the Generalized Hurst Exponent Analysis and examined the evolving market efficiency in fifteen MENA markets. The study used a rolling window technique and concluded that these equity markets had seen varying degrees of long-term dependency between 2007 and 2012, confirming the AMH.

Hiremath and Kumari (2014) and Hiremath and Narayan (2016) examined the market efficiency of the Indian Stock Market using the daily returns of the Sensex and Nifty index for the period 1991-2013. The research findings support the notion of AMH, indicating that the Indian equity market has changed over time. Parulekar (2017) examined the efficiency of the Indian equity market and discovered that it is adaptable, fluctuating between periods of efficiency and inefficiency. In parallel to this, Shahid et al. (2019) used a subsample approach and employed various linear and nonlinear tests to examine the AMH in the Pakistan stock market during the 1992–2015 timeframe. The study found that return predictability varies over time and in response to market conditions, which validated the AMH. Phan Tran Trung and Pham Quang (2019) used a time-varying approach to examine market efficiency in the Vietnam stock market. The study employed auto-regressive and autocorrelation tests over 12 years and concluded that the Vietnamese equity market confirmed the AMH, i.e., adaptive by nature. These researches have demonstrated that AMH offers a more precise financial framework for comprehending the nature of stock returns than the EMH.

Lo (2005) states that individuals act in their self-interest but make mistakes. However, the market players learn from these mistakes and adapt, and that competition drives adaptation and innovation. The AMH provides a number of practical implications. At the outset, the equity risk premium changes over time in response to the current state of the stock market and the characteristics of the investors. The second implication is that there are better and worse performance cycles for investment products depending on the industry competitiveness, investor adaptability, changing business conditions, and considerable profit potential. Third, there are occasions when the market offers opportunities for arbitrage. Therefore, from an evolutionary standpoint, it follows that actively traded financial markets must offer opportunities for profit, but that these opportunities disappear as soon as they are seized. In particular, the AMH theory supports the idea that market efficiency may fluctuate over time based on the condition of the market.

In summary, the Adaptive Market Hypothesis presents the notion that markets are adaptive where market players continuously learn and evolve, in contrast to the Efficient Market Hypothesis, which holds that markets are always efficient and that prices reflect all available information.

2.3 Market Liquidity

The second peculiarity of an efficient market is the "liquidity of its traded assets," i.e., trading efficiency. In other words, one essential aspect of the stock market is market liquidity, which ensures both the stability of the market and the tradability of assets. It is observed that numerous factors have a significant influence on asset liquidity, for instance, transaction costs, demand pressure, information on order flow, search frictions related to finding a trading partner, risk of inventory financing, and finally, negotiating a price for trading in an imperfectly competitive scenario (Amihud *et al*., 2006). It is a crucial component of the financial markets that influences price discovery, trading effectiveness, and overall market stability. Stated differently, it is essential for fostering market efficiency, attracting investors, and assuring effective risk management. In a nutshell, liquidity is one of the imperative characteristics of a financial market and is considerably vital for investment plans and financial assets.

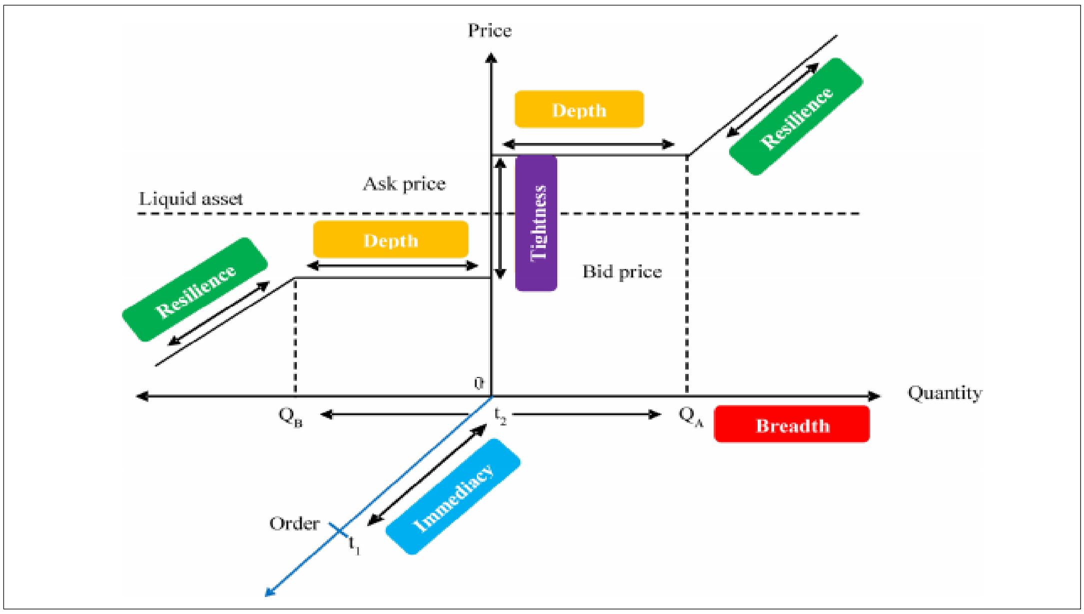
Stock market liquidity is a crucial characteristic whose presence guarantees the seamless operation of the market, while its absence causes unease among the different players in the market. It may be defined as the ease with which market participants can purchase or sell a financial instrument, such as stocks, without affecting its price (Elliott, 2015). Amihud and Mendelson (1986) defined market liquidity as the marketability of an asset and is an essential part of stock markets. Particularly, it is sometimes defined as the capacity to carry out significant transactions swiftly and at a minimal cost. In contrast to an illiquid market, where bid-ask spreads may be more significant, and price swings may be more pronounced in reaction to trade activity, a liquid market enables participants to make large trades rapidly and at a relatively low cost. Market participants, businesses, and regulators are interested in a stable level of market liquidity because it ensures that trade will continue at the appropriate prices, enables frictionless transactions, and controls the cost of acquiring capital.

Market liquidity in the stock market refers to how simple it is for investors to buy or sell an asset in a market without substantially changing the price. There is probably no single definition that is widely recognized for market liquidity. Hasbrouck and Schwartz (1988) defined it as the speed at which a trade is executed, whereas Liu (2006) defines market liquidity as the capacity to complete a trade in a substantial amount without experiencing any delay in time or impact on the price of that security. Amihud et al. (2006) pointed out that market liquidity is the state in which buyers and sellers are willing to exchange a certain quantity of assets at the agreed-upon price on a prompt basis. Brennan et al. (2012) refer to stock market liquidity as the ability of the market to absorb a huge volume of securities at a lower execution cost within a short period but without having a significant effect on security prices. Additionally, Nneji (2015) provided evidence that market liquidity demonstrates the strength of the market to absorb shocks or any economic catastrophe.

On the other hand, Panayides et al. (2013) described market liquidity as trading in securities at a lower cost than its actual worth. Kyle (1985) and Holden (1995) mentioned that the liquidity of a market can be explained in terms of three aspects, namely: depth (the quantity of securities that are traded), tightness (the costs incurred in trading security), and resiliency (the ability of the security prices to recover after a liquidity shock quickly). Furthermore, Sarr and Lybek (2002) and Bervas (2006) considered five dimensions of liquidity, including two additional dimensions:

immediacy (the time taken to execute a trade) and breadth (intensity of trading volume impact on security prices). A financial market's or asset's liquidity is a multifaceted term that is challenging to quantify using a single metric.

2.3.1 Multi-Dimensions of Liquidity



Source: Diaz & Escribano, 2020

Figure 1: Dimensions of Liquidity

The literature (Sarr & Lybek, 2002; Bhattacharya et al., 2019; Diaz & Escribano, 2020; Naik et al., 2020; Naik & Reddy, 2021a; Le & Gregoriou, 2020) highlights that liquidity can be characterized by five distinct attributes: tightness, depth, breadth, immediacy, and resiliency.

Tightness: Tightness in market liquidity is said to be present when there is a narrow bid-ask spread; to put it another way, a narrow gap between the "highest amount a buyer is ready to pay (bid) and the lowest price a seller is willing to take". A smaller spread indicates that there is less fluctuation between sellers' asking prices and buyers' willingness to pay (Sarr & Lybek, 2002; Olbrys, 2017; Olbrys & Mursztyn, 2019; Pham, 2020). It is a desirable attribute for investors, market regulators, and traders because it is generally associated with quicker execution, reduced transaction costs, and enhanced market efficiency.

Immediacy: In the context of market liquidity, "immediacy" is a critical component since it shows how quickly buyers and sellers of securities can transact at current market prices. In other words, numerous studies Sarr and Lybek (2002), Hallin et al. (2011), Wanzala (2018), Diaz and Escribano, (2020), Naik et al. (2020), Schwartz et al. (2020), Schwartz and Peng (2021) regarded immediacy as a critical element of market liquidity, indicating the speed at which trades can be completed without inadvertently moving the price. Traders, investors, and market participants carefully consider immediacy while making decisions so they can execute deals quickly and effectively while controlling transaction costs and market impact.

Depth: One crucial criterion for evaluating market liquidity is market depth. In a financial market, it gauges the volume of securities that are offered for purchase or sale. It provides information on the liquidity of a market by showing the quantity of buy and sell orders at different prices. Put differently, it displays the maximum trade volume that may be achieved at a given price. More liquidity in the trading environment results in a deeper market, but more significant transaction costs and price volatility may result from shallower market depth. According to several studies, it is an essential consideration for traders employing various strategies (Sarr & Lybek, 2002; Hallin et al., 2011; Olbrys & Mursztyn 2019; Bhattacharya et al., 2019; Naik et al., 2020; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Pham 2020; Naik & Reddy, 2021b).

Breadth: It refers to the capacity to complete a transaction in a financial market without significantly impacting the asset's price. It refers to the capacity of the market to seamlessly facilitate the trading of a certain amount of securities without significantly impacting their share prices (Sarr & Lybek, 2002; Hallin et al., 2011; Olbrys & Mursztyn 2019; Diaz and Escribano, 2020; Naik et al., 2020; Schwartz et al., 2020).

Resiliency*:* It is the capacity of a financial market to withstand shocks and continue operating normally even in the face of unfavorable circumstances or notable trading imbalances. A robust market may bounce back from shocks quickly, allowing trade to continue with little to no effect on price stability and liquidity (Sarr & Lybek, 2002; Hmaied et al., 2006; Gabrielsen et al., 2011; Bookstaber et al., 2016; Dong et al., 2017; Jha et al., 2018; Olbrys & Mursztyn, 2019; Diaz & Escribano, 2020; Pham, 2020).

Several studies (Sarr & Lybek, 2002; Bhattacharya et al., 2019; Naik et al., 2020; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Naik & Reddy, 2021a) pointed out the disadvantages of depending only on one metric or proxy to assess liquidity; i.e., there is no consensus on the most appropriate metric to use. As a result, we utilized the multifaceted concept of liquidity, which includes the five different of liquidity: tightness, depth, immediacy, breadth, and resiliency. Further, there is a dearth of research on the linkage between efficiency and market liquidity. For this reason, the EMH is examined in this study using the returns of several stocks that have been ranked according to market liquidity.

2.4 Stock Market Anomalies

Market anomalies are empirical patterns or phenomena that contradict the theory of EMH and challenge the notion of market efficiency. In other words, Stock market anomalies are financial market patterns or behaviors that violate the predictions of efficient market theory, casting doubt on the notion that markets always consider and reflect all available information.

Market inefficiencies present possibilities for investors to profit from anomalies, i.e., potentially, these anomalies suggest that certain investment strategies have historically outperformed the market over extended periods. Put another way, the theory of EMH postulates that stock prices efficiently and rapidly incorporate all available information, making it practically hard to consistently generate anomalous returns using investment strategies based on past data. Anomalies in the stock market, however, challenge this idea by showing that certain trends repeat themselves regularly, giving investors' chances to take advantage of inefficiencies in the market.

Several studies have identified anomalies that produced excess returns (Basu, 1977; Jegadeesh & Titman, 1993; Fama & French, 1993, 1996; Zhang, 2005; Hou et al., 2015). Some of the well-known market anomalies include:

Value Anomaly: This factor measures how well value stocks (those with low valuation) outperform growth stocks. Most importantly, value investing has been examined by the most prominent researchers (Basu, 1977; Chan et al., 1991; Zhang, 2005). They found an affirmative association between stocks with low prices and their fundamentals, such as sales, book value, earnings, and dividends.

The theoretical rationale for the value premium is intuitive, i.e., value firms carry a higher level of risk because they are more vulnerable to economic shocks during times of financial distress and, hence, demand a substantial risk premium (Fama & French, 1996; Zhang, 2005). Another strand of research for the value premium has been studied in the context of behavioral biases. Investors tend to extrapolate "growth stocks with past positive news" and "overreact to past negative news about value stocks," resulting in higher returns for value stocks (Lakonishok et al., 1994).

Size* Anomaly*: This factor has more exposure to smaller companies and less corresponding to the larger companies. Put another way, the size factor, also known as the "small-cap effect," asserts that companies with smaller market capitalizations frequently generate higher returns than those with larger capitalizations. Banz (1981) originated size as a factor and found that smaller companies capture relative returns corresponding to the larger ones. Various theories explain the rationale for the outperformance of the small-size effect. For instance, Fama and French (1993, 2012) proposed that small caps are exposed to undiversifiable risk, resulting in a higher premium. Other studies, in particular, argued that smaller companies are associated with financial distress, low dividends (Chan & Chen, 1991), lower liquidity (Amihud, 2002), information uncertainty (Zhang, 2006), and thus offering superior returns.

Momentum* Anomaly*: It suggests that stocks with more robust past performance substantially outperform those with lower past performance. Stated differently, stocks with better historical performance outperform those with worse historical performance. In the context of stock markets, the momentum effect is the propensity of recently performing stocks to continue outperforming while underperforming stocks are likely to continue underperforming. Jegadeesh and Titman (1993) observed that buying past outperformers and selling past underperformers generated extensive "abnormal" returns from 1965-1989 in the U.S. stock market. Rouwenhorst (1998) noted the momentum effect in twelve European stock markets: Austria, Denmark, Germany, France, Norway, Switzerland, The Netherlands, Sweden, Belgium, Spain, Italy, and The United Kingdom, during the sample period of 1978–1995. Moskowitz and Grinblatt (1999) examined the momentum effect of industry-specific portfolios in the U.S. stock market. As per their study, industry portfolios exhibit a significant momentum effect and an anomalous return that surpasses individual portfolios.

Similarly, Fama and French (2012) discovered strong persistence of momentum returns from 1989-2011. They also considered “momentum” as a robust and persistent factor that was not captured by either value or size effect. This market anomaly calls into question the efficiency theory by showing that assets exhibit persistent price changes over particular periods. Ansari and Khan (2012) used momentum strategies with three and six-month time horizons for the Indian stock market over the 1995–2006 sample periods. The research revealed a more robust momentum effect for the Indian stock market, in line with earlier findings by Sehgal and Balakrishnan (2002) and Chui et al. (2010).

The most widely cited theories underlying the momentum premium are all behavioral (Hong et al., 2000). Evidently, the theories around the momentum effect have been developed in the context of investor behavior, i.e., their over-reaction or under-reaction to new information (such as corporate results or dividend announcements). Another possible reason could be herding behavior, which occurs when profit-seeking investors create a feedback system that causes prices to drift away from fundamentals (Dasgupta et al., 2011).

Low Volatility Anomaly: The "Low volatility" premium measures the outperformance of low-volatile stocks over high-volatile stocks. Blitz and Van Vliet (2007) and Hsu et al. (2015) examined the low-volatility effect and found that low-risk stocks substantially outperformed the market benchmark. A variety of cognitive and behavioral factors may explain the low volatility anomaly and its persistence. One of the first explanations is the "lottery effect," which refers to an investor's readiness to pay a higher price for a slight chance of making a significant profit, even when losing is much higher than winning (Baker et al., 2011).

Other behavioral explanations include leverage-constrained investors seeking substantial returns in highly volatile stocks (Frazzini & Pedersen, 2014). Also, investors have a natural tendency to overestimate the performance of a few "well-publicized high-riskier stocks" and hence overpay in the hope of owning enormous returns.

Investment Anomaly: This fundamental factor is inclined towards lower investment strategies over higher investment ones. Li and Zhang (2010) and Hou et al. (2015) examined "investment" as a relatively more recent asset pricing factor in the q-theory of investment. They found that higher cash flows, greater sales growth, larger asset size, higher dividend payout ratio (D/P) and lower debt-to-asset ratio characterize the rationale behind low investment frictions. Similarly, Fama and French (2015) investigated the difference between conservative and aggressive levels of investment and concluded that lower investment levels are associated with higher anticipated returns.

Profitability Anomaly: Researchers increasingly emphasize the "profitability factor" in addition to the conventional value, size, and momentum factors. This anomaly aims to capture the "quality factor" premium by purchasing "High-profitable" companies and evading "Low-profitable" companies. The academic explanation for the profitability premium can be explained using a rational risk-based "q-theory of investment" (Hou et al., 2015).

Unlike traditional criteria that rely on market price, profitability indicators are solely based on accounting data. For instance, Novy-Marx (2013) used the gross profit margin to measure profitability. Fama and French (2015) considered operating profit as a dimension of profitability in their five-factor model. Hou et al. (2015) illustrated this anomaly by the Return on Equity (ROE).

Several studies investigated the existence of anomalies in the developed and emerging stock markets. Cakici et al. (2013) examined value and momentum anomalies in 18 emerging markets, including Eastern Europe, Asia, and Latin America. The authors found substantial evidence for the value and momentum effects in all emerging economies except in Eastern Europe from January 1990 to December 2011. Hanauer and Linhart (2015) examined three anomalies: value, size, and momentum for 21 emerging and 24 developed countries from July 1996 to June 2012. They documented a strong value effect and a considerable but less significant momentum effect. Furthermore, they found that the value component is more prevalent in emerging economies than developed markets. Agarwalla et al. (2017) examined value, size, and momentum factors in the Indian stock market over the study period of 1994 to 2017. They concluded that momentum and value are viable investments, but the size component does not outperform.

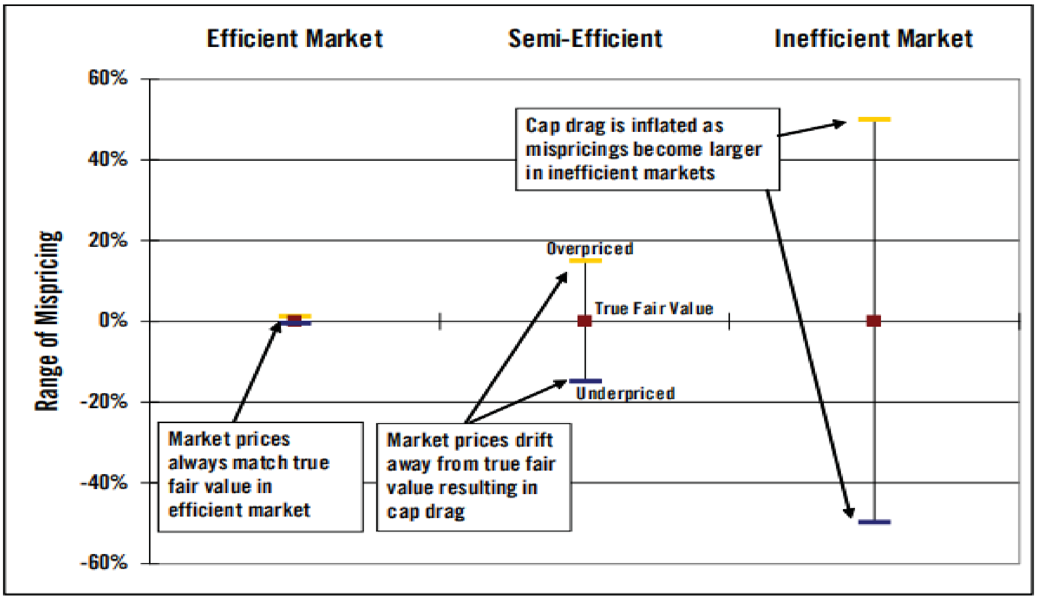
Angelidis and Tessaromatis (2017) analyzed value, low-risk, small-cap, and momentum for 23 developed and 21 emerging economies from 1980 to 2015. They found that factor portfolios exhibit superior Sharpe ratios and, in most situations, statistically significant returns when compared to world market portfolios. The authors also broadened the research by creating global factor portfolios that included emerging economies and found evidence of improved factor return efficiency.

Martellini and Milhau (2018) evaluated the six fundamental led factors from 1970-2015. They identified that these strategies outperformed the traditional index regarding the Sharpe ratio and could diversify the unrewarded risks. Bender et al. (2018) tested the five anomalies: value, profitability, investment, size, and momentum from 1963 to 2015 and reported that all these strategies delivered excess returns compared to the cap-weighted market index. In the Korean Stock Market, between 2004 and 2020, Kim (2021) presented a comprehensive examination of five factors: value, size, profitability, low risk, and momentum. The results show that all factors outperformed the market index, with the size factor generating the highest return. Silvasti et al. (2021) recently tested strategies based on momentum, value, and low beta from December 1991 to January 2019. They found that these strategies outperformed the Nordic equity market, with momentum and low beta having the highest alpha and Shape ratio.

2.5 Alternative Equity Indexing Strategies

A financial index is an aggregate indicator of a large capital market based on the values of stocks, bonds, or other financial instruments. The index contains the most relevant securities in the market and thus aims to monitor the performance of the financial market. Over the last decade, there has been tremendous development in the concept of indexing strategies that produce excess returns, usually called Alpha. When searching for these returns, investors face two options: either using their information to obtain additional value, known as active investment, or following the market by investing in the market portfolio, known as passive Investing (Bender et al., 2013).

Although there are several ways to weight indices, such as price-weighted, value-weighted, and capitalization (cap)-weighted, but cap-weighted indices are widely used as market indices worldwide. In these conventional cap-weighted indexes, the market cap of each security determines its weight in relation to the total market capitalization of all the stocks in the index. However, a number of studies observed several shortcomings in these conventional cap-weighted indices. Initially, these indices are highly concentrated, meaning that a substantial amount of the market index was made up of only a few names (Tabner, 2009; Malevergne et al., 2009; Demey et al., 2010; Amenc et al., 2012a, 2014; Russo, 2014). The construction mechanism of these indices only accounts for one dimension (market cap) and, as a result, does not provide adequate diversification. According to Treynor (2005), Hsu (2006), Arnott & Hsu (2008), another possible drawback of the cap-weighted market index is that it causes a return drag on portfolios, which renders it sub-optimal than the non-cap-weighted indices. Stated differently, empirical evidence suggests that cap-weighted market indices lack proficiency and diversification, resulting in poor adjusted returns (Ferson et al., 1987; Haugen & Baker, 1991; Grinold, 1992; Amenc, 2011; Goltz & Le Sourd, 2011; Amenc et al., 2016; Centineo & Centineo, 2017).



Source: Arnott, and West, 2006

Figure 2: Return Drag of Cap-Weighted Indices

Over the past ten years, there has been exponential growth in the field of alternative equity indexation. A review of previous research on well-known and noteworthy diversified indexing strategies is provided in this section. It has been observed by Haugen and Baker (1991), Clarke et al. (2006, 2011), Demey et al. (2010), Amenc et al. (2012b), and more recently, Cai et al. (2018) that the minimum variance strategy outperforms the cap-weighted index in terms of returns, volatility, and risk-adjusted results. Choueifaty and Coignard (2008) examined the theoretical and empirical characteristics of three prominent strategies between 1992 and 2008: minimum variance, equal weighting, and most diversified portfolio (MDP) across the U.S. and the Eurozone. Consequently, the study reported that these strategies outperformed the traditional cap-weighted indexes in terms of risk-adjusted performance.

Demey et al. (2010) examined the performance of four diversified strategies- equal-weighted risk contribution (ERC), minimum variance, maximum deconcentration, and maximum shape ratio -against conventional market indices. They found that these strategies are better diversified and more efficient. Maillard et al. (2010) and Plyakha et al. (2012) show that equal-weighted portfolios outperformed market portfolios empirically in terms of performance and diversification. In their study, Amenc et al. (2011) employed efficient indexation and presented empirical findings indicating a greater Sharpe ratio in comparison to market cap weighting. Moreover, their analysis continued to hold over a range of time periods, market conditions, and levels of uncertainty. From 1959 to 2010, Amenc et al. (2012b) examined three different strategies: minimum variance, maximum Sharpe ratios, and the diversified multi-portfolio. According to their analysis, these portfolios outperformed the cap-weighted S&P 500 index.

Amenc and Goltz (2013) examined the performance of four strategies, including minimum variance, maximum decorrelation, maximum Sharpe Ratio, and maximum deconcentration, during ten years, from 2002 to 2012. Their study consistently found the outperformance of these strategies over the S&P 500 market index. Parallel to this, Clarke et al. (2013) investigated three optimization-based strategies from 1968 to 2012. In comparison to the U.S. market index, the analysis showed that minimum variance, risk parity, and maximum diversification strategies performed better. Monga et al. (2021, 2022) tested different factor-based and optimization-based investment strategies in the emerging Indian equity market and found evidence of better risk-adjusted performance and diversification.

Since there is a lack of empirical evidence in the context of emergent financial markets, this study takes into account the emerging Indian equity market for a number of reasons: foremost, alternative indexing is more prevalent in developed markets than in emerging ones, and no research has been done on these alternative indexing strategies in the Indian Stock Exchange. Second, India, an emerging economy with distinct characteristics and structural issues, could offer a distinctive viewpoint on indexing strategies and policy measures. Third, the Indian emerging-market stock market has been growing significantly regarding the quantity of securities, international participation, and market capitalization. To fill this gap and give market participants a more thorough understanding, this study offers valuable insights regarding the performance of alternative indexing in the emerging Indian equity market.

Chapter 3
Research Methodology

CHAPTER 3
RESEARCH METHODOLOGY

This chapter will cover the specific research methodology that was employed to accomplish the distinct research objectives.

The study developed the following research objectives, which were accomplished utilizing a variety of approaches and techniques based on the existing review of the literature and theoretical framework.

Objectives of the Study

The research objectives for the study are stated as follows:

- To examine the weak-form market efficiency of the Indian Stock market
- To explore the linkage between market Liquidity and efficiency
- To study the presence of different anomalies in the Indian Stock Market
- To construct and evaluate the performance of alternative equity indexing strategies

3.1 Objective 1: To examine the weak-form market efficiency of the Indian Stock market

The study looked into weak-form market efficiency (both absolute and evolving) using linear and non-linear tests such the Runs test, Autocorrelation test, Variance Ratio test, Bartel test and BDS test.

3.1.1 Sample, Time Period, and Data Sources

The S&P NSE 500 composite index, which comprises a diverse range of companies with different market capitalizations, was chosen as the representative stock market (Cap-weighted benchmark). The sample period for the study is from June 1999 to December 2022. Every dataset pertaining to market index has been taken from the Bloomberg database.

The daily return for the index is calculated as follows:

$$\mathrm{R}_t = \ln P_t - \ln P_{t-1} \tag{1}$$

Where, R_t is the daily index return at time t, lnP_t and lnP_{t-1} are the natural logarithm of the closing price at time t, and $t - 1$ respectively

3.1.2 Methodology for testing Weak-Form Efficient Market Hypothesis

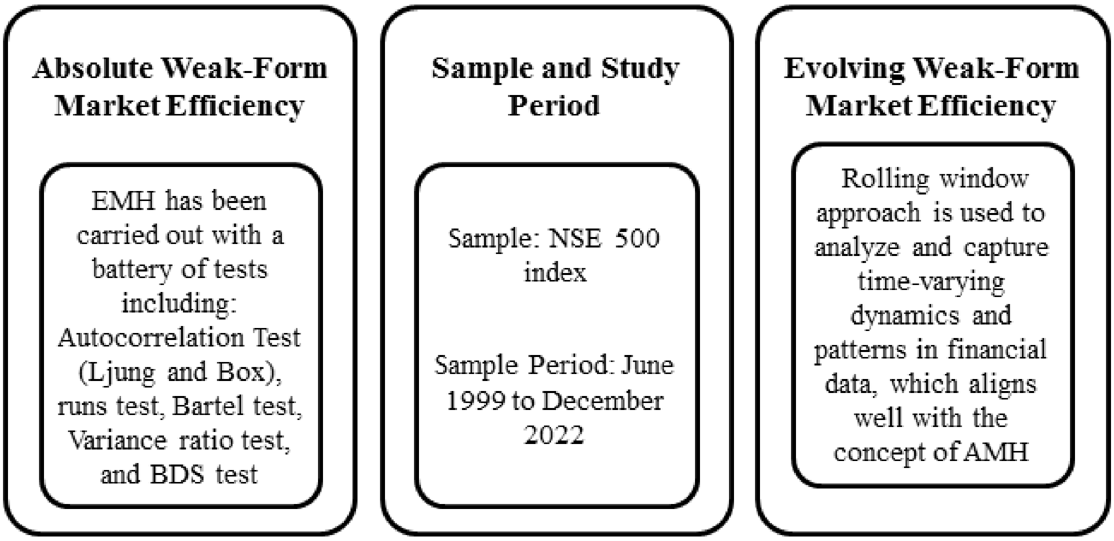


Figure 3: Framework for testing Absolute and Evolving Weak-Form market efficiency

The study of EMH, as proposed by Fama (1970), is a critical concept in finance. An efficient market is one in which asset values are not predictable since the prices already represent the information and quickly respond to any new information. In the current study, the analysis of EMH has been carried out with a battery of tests (Urquhart, 2016), including Ljung and Box, runs test, Bartel test, Variance ratio test, and BDS test.

The weak-form market efficiency has been investigated using two hypotheses, which are as follows:

H_0: Return series follows a random walk, i.e., the market is weak-form efficient.

H_1: Return series does not follow a random walk, i.e., the market is weak-form inefficient.

Autocorrelation Test

It is an appropriate and reliable technique for examining the independence of a series of random variables. In other words, the probability of serial correlation in stock returns can be investigated using various statistical methods, such as autocorrelation tests. If a set of returns shows signs of autocorrelation, they cannot be considered as independent. On the other hand, the absence of autocorrelation in a series does not inherently indicate its independence; instead, it merely suggests the absence of linear dependencies within the series. Autocorrelation tests are a crucial tool for evaluating the efficiency of stock markets when considering the EMH. The weak form of market efficiency states that stock prices accurately reflect all available historical information. As a result, stock returns exhibit a random walk, indicating the absence of autocorrelation.

It is a valuable and accurate tool for determining the independence of a set of random variables with a null hypothesis of no correlation (p=0). Statistically, Positive autocorrelation is indicated by $p > 0$, and negative autocorrelation is shown by $p < 0$.

If autocorrelation exists, returns are influenced by their preceding values. However, when the returns are independent, the series shows no signs of autocorrelation, signaling that the time series follows a random walk process. We used the Ljung-Box (Ljung & Box, 1978) test to look at the autocorrelation of returns:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{p}_k^2}{n-k} \tag{2}$$

Where, $\hat{p}_k$ indicates the autocorrelation of order k, *k* is the number of lags, and *n* denotes the sample size.

Runs Test

Second, the runs test is a simple yet powerful tool for analyzing the unpredictability (or predictability) of financial time series. This approach is categorized as non-parametric and is used to evaluate the randomness of time series, particularly those that are not normally distributed. Numerous research studies have observed that the runs test is commonly employed in combination with multiple other tests to assess market efficiency. The idea behind the test is to determine whether the direction of one observation affects future observations. In other words, the purpose of this test is that if the time series is randomly fluctuating and independent, the number of actual runs should be identical to the expected number of runs in the series. The number of expected runs is calculated using the formula below:

$$\text{Expected Number of Runs} = \frac{2PN(P+N)}{(P+N)} + 1 \tag{3}$$

Where, *P* represents positive runs and *N* indicates Negative runs.

The following formula can be used to determine variance:

$$\sigma^2 = \frac{2PN\left(2PN - P - N\right)}{\left(P+N\right)^2\left(P+N-1\right)} \tag{4}$$

Bartels Test

Furthermore, to determine the randomness of the series, the third test is the Bartels (1982) test, which is a rank variant of von Neumann's Ratio Test for Randomness. This non-parametric test is equivalent to the Run test but is considered to be more effective in ascertaining if a set of observations or series is random. In other words, it is used explicitly in finance and econometrics to determine if the observed values in a given series are randomly distributed or show signs of a systematic pattern. Specifically, it employs independence as the null hypothesis, i.e., determining whether returns are independent or not. In light of this, if any of these tests reject the null hypothesis, stock returns can likely be forecast using historical data, indicating that weak-form market efficiency is not being followed.

Variance Ratio Test

Apart from the tests mentioned above, the most frequently utilized econometric instrument for assessing the RWH is the Variance Ratio (VR) Test, developed by Lo and Mackinlay (1988). It is a popular method for investigating serial independence under the random walk or martingale null hypothesis, which states that the returns are serially uncorrelated. To implement the VR test, we utilized Choi's (1999) automatic variance test (AVR) in conjunction with wild bootstrap Kim (2009) to improve the small sample properties.

$$\mathrm{VR}\left(K\right) = 1 + 2\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)p_j \tag{5}$$

Where, k represents the holding period, p_j denotes the autocorrelation of return in order j.

Nonlinear patterns cannot be found in the return series using linear tests like runs test, bartel, test, autocorrelation, and variance ratio tests. Given the non-normality of the series, the failure to reject linear dependency does not necessarily imply independence Granger and Anderson (1978); Hsieh (1989, 1991). The EMH is refuted by the existence of nonlinearity in equity returns. Predominantly, nonlinearity is a sign of predictability and perhaps extra profits for the market participants, and in these situations, applying linear models could lead to the incorrect conclusion. As a result, the BDS test was utilized to investigate the potential for nonlinear dependence.

BDS Test

Next, we employed the BDS test for serial dependence, which is one of the most prominent and extensively used non-parametric tests (Broock et al. 1996). The null hypothesis asserts that data generation mechanisms are "independent and uniformly distributed," whereas the alternative hypothesis holds that "the model is unspecified." Following Lim and Hooy (2013) and Urquhart (2016), we chose embedding dimension (*m*) ranging from 2 to 5, and ε/σ is 1, i.e., one times the standard deviation of the returns.

$$\mathrm{W}_{m,n}(\varepsilon) = \sqrt{n}\,\frac{T_{m,n}(\varepsilon)}{V_{m,n}(\varepsilon)} \tag{6}$$

Where, $\mathrm{W}_{m,n}(\varepsilon)$ represents the BDS statistics, *m* is the embedding dimension, *n* denotes the sample size, and (ε) is the metric bound, the largest difference between the observation pairs while calculating the correlation integral. In accordance with the literature (Urquhart & McGroarty 2016), we computed the mean of the p-values derived from the m-values to find out how the predictability changes over time.

Given the complexity and dynamic nature of financial markets, the inclusion of non-linear models enables a more realistic portrayal of market behavior. As a result, identifying non-linearity in stock returns is essential for enhancing investing strategies, comprehending risk dynamics, and creating more accurate financial models.

3.1.3 Testing of Adaptive Market Hypothesis

Furthermore, the study investigated the evolving market efficiency for the Indian stock market. In order to achieve this, the research analyzed and captured time-varying dynamics and patterns in financial data using the rolling window technique. Particularly, the rolling window approach divides the entire time series data into a sequence of overlapping periods. In other words, it involves data over consecutive, overlapping time periods (windows) to capture how market behavior, patterns, and relationships evolve over time. This approach aligns well with the concept of adaptation in the AMH. In contrast to earlier research, which frequently used subsample analysis, the study considered rolling window analysis with the 500 observations (approximately two years) that roll one month forward to precisely capture the evolving efficiency (Todea et al., 2009; Smith, 2012; Urquhart & McGroarty, 2014, 2016, Dhankar, 2019; Shah & Bahri, 2019; Kılıç, 2020; Okorie & Lin, 2021, Aleknevičienė et al., 2022; Bassiouny et al., 2023) . In addition, moving window analysis progressively illustrates how predictability varies over time in place of subsample analysis. To put it another way, the primary flaw with subsample analysis is the prejudice involved in choosing the subset, which could have distorted the results. Afterward, a range of linear and non-linear tests, including the runs test, variance ratio test, autocorrelation test, Bartel, and BDS tests, were applied to the rolling returns to analyze the adaptive market efficiency.

3.2 **Objective 2:** To explore the linkage between market Liquidity and efficiency

The study made use of the multifaceted notion of liquidity, which includes the five distinct multi-dimensions: tightness, resiliency, depth, breadth, and immediacy. Additionally, there is a paucity of research on the linkage between efficiency and market liquidity. For these reasons, the Efficient Market Hypothesis is examined in this study using returns from a number of equities that have been classified based on market liquidity.

3.2.1 Sample, Time Period, and Data Sources

For this study, we chose 500 stocks from the NIFTY 500 index of the NSE (National Stock Exchange of India). However, we used a dataset of 485 stocks available during the study period of June 2008–December 2022. The entire dataset was retrieved from Bloomberg, including daily data on closing share prices, number of shares outstanding, trading volume, and bid and ask prices. The daily return for the stock is calculated as follows:

$$\mathrm{R}_t = \ln P_t - \ln P_{t-1} \tag{7}$$

Where, R_t represents the daily stock return at time t, lnP_t and lnP_{t-1} are the natural logarithm of the closing price at time t, and $t-1$ respectively.

3.2.2 Testing Multi-Dimensions of Liquidity

Stock market liquidity is a vital component to consider when making investment decisions. It affects the ease of buying and selling securities, impacts transaction costs, and can influence the execution of investment strategies. It is noted that different authors have conceptualized market liquidity differently in the literature (Sarr & Lybek, 2002; Bhattacharya et al., 2019; Naik et al., 2020; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Naik & Reddy, 2021a). As a result, measuring market liquidity has proven to be challenging for earlier research.

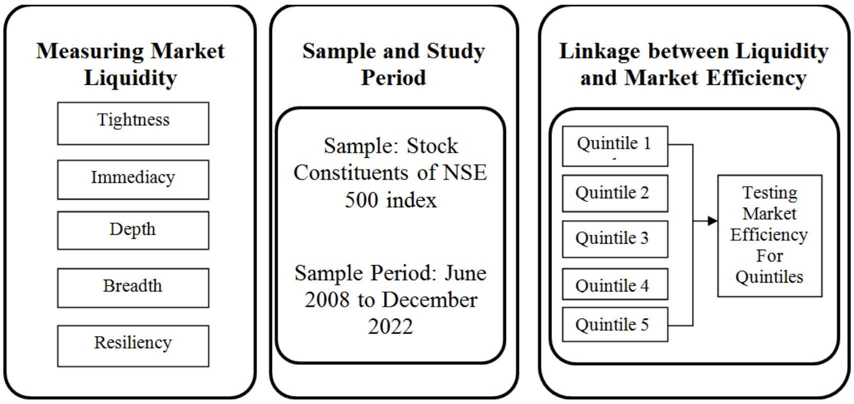


Figure 4: Testing Multi-Dimensions of Market Liquidity and its linkage with Efficiency

It is evident from the body of existing research that there is no consensus to quantify liquidity, and as a result, various studies have utilized different metrics for the same. To account for the diverse nature of market liquidity, we used a multi-dimensional approach that includes the five dimensions: tightness, depth, immediacy, breadth, and resiliency, as suggested by Sarr and Lybek (2002). The following is a list of the proxies for different dimensions:

Tightness: It is the term used to describe the bid-ask spread, which is the important aspect of market liquidity. It is a characteristic of transaction costs that is represented by the difference in ask and bid prices. To quantify tightness, the study used the Closing Percent Quoted Spread (CPQS) developed by (Chung & Zhang, 2014). It is calculated using daily closing bid-ask prices and is recognized as the most widely utilized proxy measure for the effective bid-ask spread by previous studies (Fong *et* *al*., 2017; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Naik et al., 2020).

$$\text{Relative Quoted Spread } (RQS) = \frac{\text{Ask Price}_{it} - \text{Bid Price}_{it}}{\left(\text{Ask Price}_{it} + \text{Bid Price}_{it}\right)/2} \tag{8}$$

Immediacy: It refers to the simplicity and speed with which the process of trade can be well-accomplished and settled (Tripathi et al., 2019). It displays the settlement structure, coherence of trading systems, and the speed at which orders are executed. In other words, it relates to the amount of time both parties will need to complete the stated quantity of a security at the agreed-upon price.

To quantify market immediacy, Wanzala (2018) and Naik et al. (2020) used the Coefficient of Elasticity of Trading (COE), which accurately portrays the speed with which a trade is executed. The following formula is used to calculate it:

$$\text{Coefficient of Elasticity of Trading } (CET) = \frac{\%\Delta T}{\%\Delta P} \tag{9}$$

Where, $\%\Delta T$ and $\%\Delta P$ represents the percentage changes in daily trading volume and closing price, respectively.

Depth: It demonstrates the market's ability to accommodate a vast number of orders to maintain stock price equilibrium. In other words, one way to quantify liquidity is by market depth, which represents by the amount of buy and sells orders at various price points. More liquidity is available in a deep market with many orders at different price points. The depth of the market promotes market efficiency by facilitating more seamless trade execution, which lessens the effect of huge transactions on prices.

In this approach, the number of stocks traded in the entire market is critical for the survival of a deeper market (Vo & Batten, 2010; Bhattacharya et al., 2016; Tran et al., 2018; Naik et al., 2020; Naik & Reddy, 2021). It is calculated using Equation 8:

$$\text{Share Turnover } (ST) = \frac{VO_t}{SO_t} \tag{10}$$

Where, VO_t and SO_t represent the volume of stocks and shares outstanding at time t, respectively.

Breadth: It describes the capacity of the financial market to seamlessly facilitate the trading of a specific volume of securities without significantly impacting their share prices. For analyzing the dimension of breadth, we utilized the Amihud Illiquidity Ratio, which was proposed by Amihud (2002) and has been considered the best price impact metric by earlier studies (Gabrielsen et al., 2011; Diaz & Escribano, 2020; Le & Gregoriou, 2020; Naik et al., (2020). This ratio shows how the price of a security changes when its volume changes. The following formula is used to compute it:

$$\text{Amihud Illiquidity Ratio } (AR) = \frac{|R_{it}|}{Vol_{it}} \tag{11}$$

Where R_{it} stands for absolute return on day t for stock i, and Vol_{it} represents Volume in (value).

Resiliency: It is a market characteristic in which new trade orders flow quickly to fix trading imbalances, and prices tend to revert to intrinsic value (Sarr & Lybek, 2002; Hmaied et al., 2006; Bookstaber et al., 2016; Bhattacharya et al., 2016; Dong et al., 2017; Jha et al., 2018; Olbrys & Mursztyn, 2019; Pham, 2020). Hasbrouck and Schwartz (1988) suggested the Market Efficiency Coefficient (MEC) as a way to discern short-term price changes from long-term price changes, i.e., the variances of two returns with distinct time durations. Following Sarr and Lybek (2002) and

Bhattacharya et al. (2019), we considered five-day returns as a longer period and daily returns as a short term, and thus, T equals 5 for our study. The statistic is close to one in liquid markets, but large deviations from one indicate a lack of liquidity. The following formula is used to compute MEC:

$$\text{Market Efficiency Coefficient}=\frac{\text{Long period log return variance}}{\text{T}\times\text{Short period log return variance}} \tag{12}$$

Where, *T* stands for the number of short periods within each longer period.

3.2.3 Linkage between Market Liquidity and Efficiency

After that, our study examined the connectedness of market liquidity and efficiency, i.e., the EMH is being tested on the returns of several stocks sorted for market liquidity. In other words, to ascertain the linkage between liquidity and efficiency, the weak form of EMH is being examined for five different quintiles that are classified by depth ratio. Predominantly, we followed the methodology of Naik et al. (2020) to divide the stock universe into five quintiles based on the Depth ratio, with the 1st Quintile (upper quintile) being the most liquid and the 5th Quintile (lower quintile) is being the least liquid. This procedure is being used to evaluate how closely liquidity and efficiency are related. In a nutshell, the study closely followed Wei (2018) for a set of statistical tests for randomness and noted the quintile-based p-values for each efficiency test for the five stock groups.

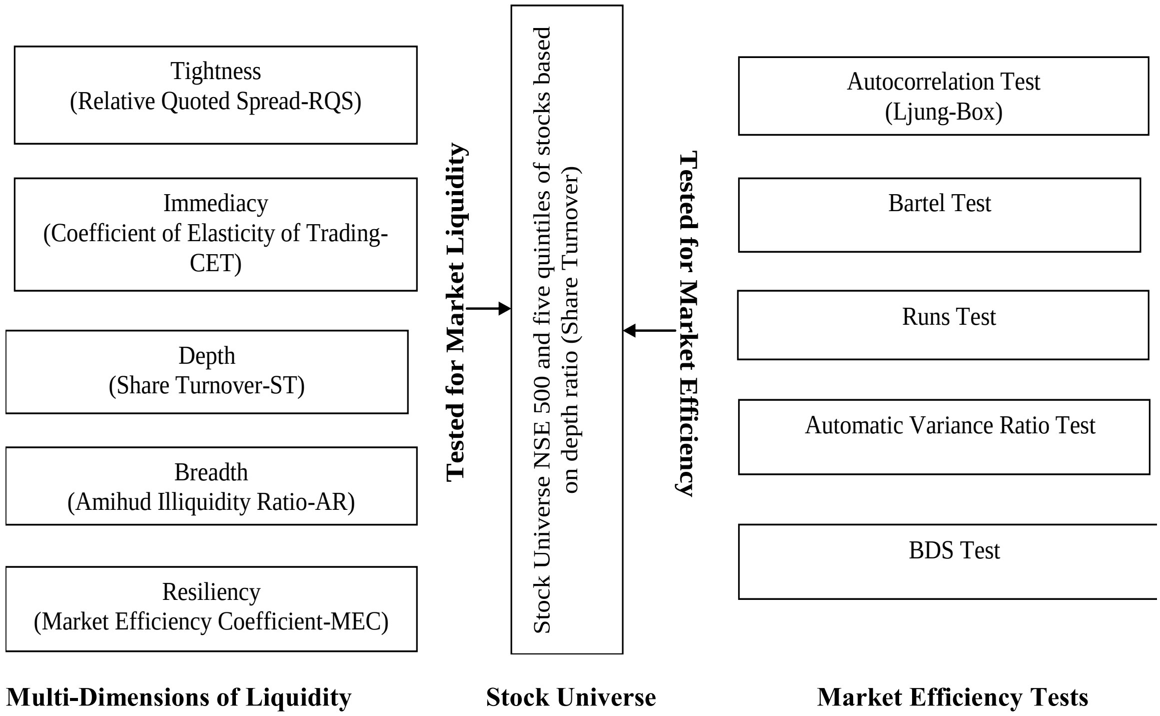


Figure 5: Outline for Testing Market Liquidity and Efficiency

During the sample period, each quintile included a total of 97 stocks, with each quintile allowed to vary based on the yearly rankings of their share turnover (ST) ratio. To compute aggregate market liquidity, we converted daily stock-specific data into weighted cross-sectional averages based on the daily market cap of the stocks. Subsequently, the daily averages of these liquidity measurements were transformed into natural log values to eliminate outliers. Last of all, these log values were used to generate the overall market liquidity results.

3.3 Objective 3: To study the presence of different anomalies in the Indian Stock Market

Stock market anomalies are empirical patterns or anomalies that seem to contradict the idea of EMH and can be exploited as investment strategies. These anomalies represent situations where certain stocks or groups of stocks consistently exhibit abnormal returns beyond what would be expected based on their risk levels. Investors and researchers have identified several well-known stock market anomalies that can potentially be used as investment strategies.

3.3.1 Sample, Time Period, and Data Sources

The anomalies were tested using the NSE 500 Stock universe from July 1, 2003, to June 30, 2020. This data period was chosen in light of the history of structural and economic downturns encountered by Indian stock markets, which includes the financial crisis of 2007–2008, demonetization in 2016, the introduction of the Goods and Services Tax (GST) in 2017, and most recently, the COVID-19 pandemic. Furthermore, the selected sample period includes 204 monthly observations, encompassing both bull and bear market circumstances. The study employs the approach of Fuller and Goldstein (2011), which splits the sample period into two halves, referred to as bull and bear. The bear sample consists of 78 months, corresponding to the period of negative market returns, while the bull sample consists of 126 monthly observations or positive market returns. This type of analysis is essential for investors who wish to know how their portfolio behaves in different market scenarios and how that behavior affects the performance of their portfolio. Except for momentum, which is rebalanced semi-annually, all other anomaly-based investment strategies undergo an annual rebalancing process. Apart from that, the performance of portfolios is calculated each month and held onto the portfolio until the following rebalancing period. All relevant data is gathered using the Bloomberg database.

3.3.2 Methodology for testing Stock Market Anomalies

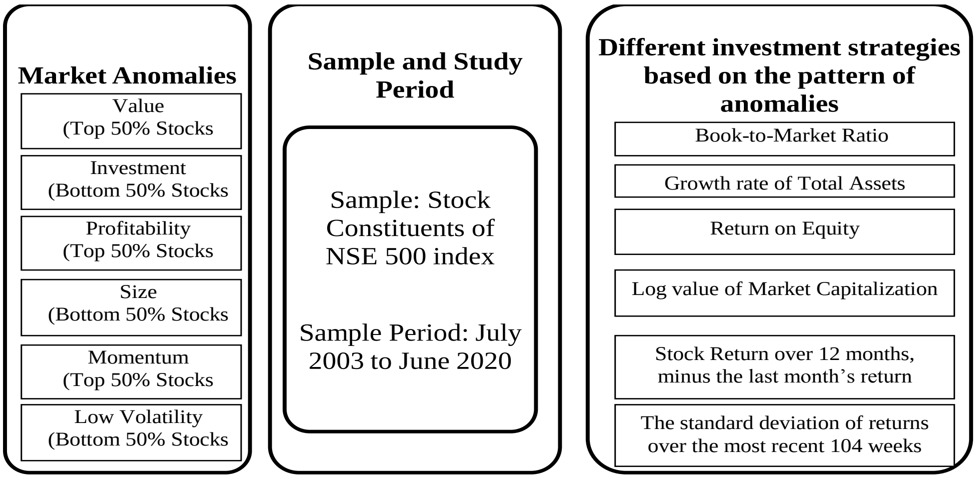


Figure 6: Methodology for testing Market Anomalies

Our analysis considered six investment strategies based on the pattern of market anomalies: value, size, momentum, low volatility, profitability, and investment. There is extensive literature that supports that these factors are validated by theoretical and empirical evidence and can prompt robust out-of-sample results (Fama and French, 1992, 1993, 2015; Jagadeesh and Titman, 1993; Amenc et al., 2015; Chow et al.,, 2018). The details of the following are provided in Table 1:

Table 1: Framework for constructing market anomalies:

Market Anomaly	Measure	Signal	Supported Literature
Value (HML)	Book-to-Market Ratio (B/M)	High	Cakici et al., 2013; Hsu et al., 2015; Blitz, 2016; Hu et al., 2019
Investment (INV)	The two-year growth rate of Total asset	Low	Hou et al. (2015); Blitz 2016; Bender et al. 2018
Profitability (PROF)	Return On Equity	High	Hou et al. (2015); Hsu et al. 2015
Size (SMB)	Log value of Market Capitalization	Small	Cakici et al. 2013; Hanauer and Linhart 2015; Hou et al. (2015); Bender et al. 2018
Momentum (MOM)	Stock return over 12 months, minus the last month's return.	High	Hanauer and Linhart 2015; Blitz 2016; Agarwalla et al. 2017
Low Volatility (LVOL)	The standard deviation of returns over the most recent 104 weeks.	Low	Hsu et al. 2015; Centineo and Centineo 2017

The details of the construction of different investment strategies based on the pattern of anomalies are as follows:

Value* Anomaly*: Stocks are sorted by their high to low B/M ratio, and after that, select the Top 50% to explore the value tilt.

Size* Anomaly*: The bottom 50% of stocks are selected as per the log value of market capitalization.

Momentum* Anomaly*: This strategy looks into the Top 50% of stocks based on the returns over 12 months, skipping the most recent month.

Investment* Anomaly*: First, stocks are arranged as per the Two-year growth rate of total assets. Afterward, the stocks from the bottom 50% are selected to get exposure to low investment.

Low Volatility Anomaly: This tilt utilizes the standard deviation of stock returns during the most recent 104 weeks. Afterward, the Bottom 50% of stocks is selected as per this criterion.

Profitability* Anomaly*: To explore this strategy, the Top 50% of stocks are picked up as per the ROE signal.

To evaluate the robustness, performance, and consistency of these anomalies, the study tested the portfolios by implementing the following three notable and effectual types of weighting schemes. A summary of the weighting schemes is provided below:

Risk Parity Weighting (RP): This strategy is recognized as the "Diversified Risk-Weighted" strategy based on the phenomenon that each stock has an equivalent risk contribution to the portfolio. This strategy is assumed to attempt to reduce risk concentrations by allocating large weights to less risky stocks while moving away from riskier ones. This method is used as a proxy for Inverse Volatility Strategy, and thereby, weights are inversely proportional to the stock's volatility (Chaves et al., 2011; Russo, 2014). Equation (13) is used to determine the weights:

$$W_i = \frac{{\sigma_i}^{-1}}{\sum_{i=1}^{n} {\sigma_i}^{-1}} \tag{13}$$

Where w_i represents the weight of i^{th} stock; n denotes the number of stocks; σ_i stands for i^{th} stock's volatility.

Factor Weighting (FW): This strategy follows a methodology that ranks stocks based on their factor criteria. For instance, the B/M ratio is used to capture value tilt. Likewise, other factors are formulated as per the desired measurement criteria (Table 1). Following that, the strategy assigns Z-scores to all the stocks with desired factor attributes. Consequently, the calculated Z-factor scores are then transformed into Standardized factor scores (S-factor scores) by normalizing them between 0 and 1 (refer to Appendix A). Finally, for calculating stock weights, a common practice is adopted by various factor index providers, i.e., adjusting market cap weight to the normalized S-factor scores. Hence, the final weights are calculated as per Equation (14):

$$W_i = \frac{S_i \times MC_i}{\sum_{i=1}^{n} S_i \times MC_i} \tag{14}$$

Where, S_i is the standardized factor score of i^{th} stock and MC_i is the market cap-weight of i^{th} stock.

Equal Weighting (EW): It is perceived as a strategy with only one parameter: the number of stocks. This approach gives each stock the same weight, thereby avoiding the large-cap tendency while also taking advantage of smaller companies. It is utilized as a proxy for the diversified weighting plan (Chaves et al., 2011; Amenc et al., 2017). It is determined as per Equation (15):

$$W_i = \frac{1}{n} \tag{15}$$

Where, *n* is the number of stocks.

3.4 Objective 4: To construct and evaluate the performance of alternative equity indexing strategies.

Alternative equity indexing strategies refer to approaches that deviate from traditional market-cap-weighted indexing. These strategies seek to lower risk, improve portfolio performance, or align with specific investment objectives. Optimization-based alternative equity indexing strategies build portfolios with specific desirable attributes by applying mathematical optimization approaches.

3.4.1 Sample, Time Period, and Data Sources

The S&P NSE 500 composite index, which comprises a diverse range of companies with different market capitalizations, was chosen as the representative stock market (Cap-weighted benchmark). As a result, the alternative equity index strategies are applied to the S&P NSE 500 stock index throughout the sample period from April 1, 2004, to March 31, 2020. The 91-days Treasury bill rate is considered as the proxy for the risk-free rate. Every dataset pertaining to market index has been taken from the Bloomberg database.

Besides this, the study also simulates the performance of the optimized strategies with semi-annual rebalancing in April and October each year. As a result, for testing the performance of these strategies, their optimal weights are obtained during each semi-annual period, thereafter hold the portfolio until the next rebalancing period, and finally reported their monthly returns.

3.4.2 Optimization-Based Alternative Equity Indexing Strategies

This section discusses optimization-based weighting strategies and the norm constraints of these strategies. Particularly, the study offers valuable information on the effectiveness of alternative indexing in the emerging Indian stock market and provides more detailed insight for different market participants.

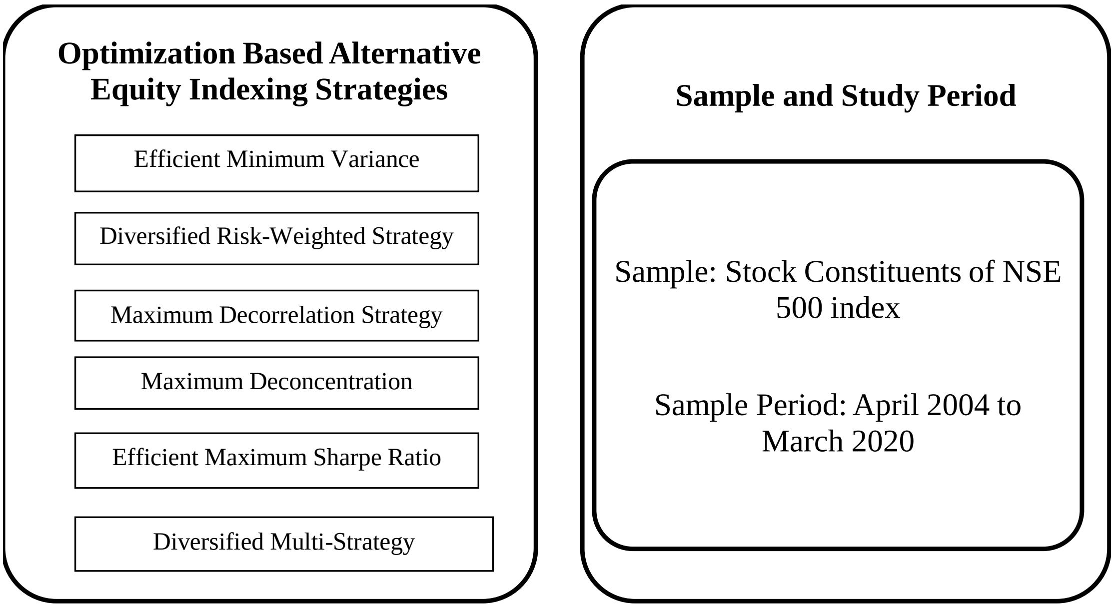


Figure 7: Framework for constructing Optimization based Alternative Equity Indexing strategies

As described in the introduction, the study focused on the following notable and effective alternative weighting strategies: Efficient Minimum Variance, Diversified Risk-weighted, Maximum Decorrelation, Maximum Deconcentration, Efficient

Maximum Sharpe ratio, and Diversified Multi-Strategy. The details of optimization-based alternative equity indexing strategies are as follows:

Efficient Minimum Variance

Efficient Minimum Variance (EMV) strategy is a portfolio strategy that minimizes risk in portfolio construction. It is portrayed as a remarkable strategy aimed at achieving the lowest possible volatility in the portfolio. The Modern Portfolio Theory (MPT), created by Harry Markowitz, is the foundation of this technique and highlights the significance of diversification in obtaining ideal risk-return profiles. In other words, it is an optimal portfolio that aligns with "modern portfolio theory," which aims to attain the least amount of risk among all available portfolio options. Predominantly, this strategy addresses a desirable aspect for risk managers, mainly when the expected returns include a significant estimated risk. Eq. 16 is used to determine the optimum weights:

$$\begin{aligned} w^{MV} &= Min\ w^{T} \Sigma w \\ & s.t. \\ & \sum_{i=1}^{N} w_i = 1, \\ & w_i \geq 0 \end{aligned} \tag{16}$$

Where w^T denotes the transposed weight vector; i is the i^{th} stock; N stands for the number of stocks; w_i represents the weight of each stock and $\sum$ is the covariance matrix for returns. This strategy is solely based on the covariance matrix, which is estimated using the previous year's daily returns.

Diversified Risk-Weighted Strategy

An investment technique, a diversified risk-weighted strategy, seeks to build a portfolio by considering risk weighting and asset diversification. In other words, this strategy considers both diversification and the risk attributes of each asset when allocating it to the portfolio. This approach entails distributing assets in a way that balances the risk attached to each asset with the goal of maximizing returns. The strategy is particularly relevant for investors who wish to control risk while maintaining a well-balanced portfolio.

This strategy is based on a particular case of the general Risk Parity approach that seeks to equalize the individual stock contributions to the index's overall risk. Put another way, weights are applied to stocks based on the level of risk; that is, lower weights are given to riskier stocks, and higher weights are given to equities with lower volatility. By accounting for volatility, the strategy removes risk concentration and creates a more balanced risk profile. The weights are determined as per Eq.17:

$$w^{DRW} = \frac{\sigma_i^{-1}}{\sum_{i=1}^{N} \sigma_i^{-1}} \tag{17}$$

Where σ_i is ith stock's volatility

Maximum Decorrelation Strategy

It is closely associated with the minimum variance portfolio (Christoffersen et al., 2012), but instead of reducing variance, it seeks to minimize the correlation between securities. When referring to investment portfolios, maximum decorrelation means creating a portfolio where the individual assets have the least correlation with one another. This strategy seeks to reduce volatility, increase portfolio diversification, and mitigate the detrimental effects of market fluctuations on the portfolio.

Instead of employing a covariance matrix, this strategy uses only the correlation matrix as its primary input, thereby decreasing the input parameters. Furthermore, this strategy assumes that the volatility of an individual asset is similar and, thus, avoids the possibility of error in assessing anticipated returns and volatility of individual securities. The following optimization problem is used to calculate the optimal portfolio weights (Eq.18):

$$w^{MD} = Min\ w^T A w \quad \text{s.t.} \quad \sum_{i=1}^{N} w_i = 1, \quad w_i \geq 0 \tag{18}$$

Where A, denotes the correlation matrix for returns

Maximum Deconcentration

This strategy entails avoiding an undue concentration of investments in one industry, asset class, or region. In other words, to lower the risk of concentration, it is preferable to distribute investments throughout a range of assets rather than concentrating a sizable portion of the portfolio in one.

This strategy is perceived as a modified version of "equal weighting," in which each stock in the portfolio is given the same weight. Typically, it re-weights the stocks in a conventional cap-weighted index, minimizing the firm-specific risk. Put another way, this approach equalizes all the stocks' weights, thus evading the problem of "overweight the overpriced stocks and underweight the underpriced stocks." The following is the description of the optimization problem (Eq.19):

$$w^{\text{Max Dec}} = Max \frac{1}{w^T w} \quad \text{s.t.} \quad \sum_{i=1}^{N} w_i = 1, \quad w_i \geq 0 \tag{19}$$

Efficient Maximum Sharpe Ratio

Efficient Maximum Sharpe Ratio (EMSR) aims to maximize the Sharpe Ratio and optimize the risk-return profile of a portfolio. Particularly, this approach is based on the MPT (modern portfolio theory) of Harry Markowitz, which highlights the value of diversification in achieving the best risk-return profiles. Stated differently, a standard metric in finance is the Sharpe Ratio, which evaluates an investment's or portfolio's performance after adjusting for risk. It is calculated using the excess return over the risk-free rate divided by the excess return's standard deviation.

This strategy seeks to achieve the best possible risk-adjusted outcome based on projected returns and volatility. It depends on projections of risk parameters (volatility and correlation) and expected returns compared to minimum volatility strategies that only include estimates of risk parameters. Moreover, the strategy would yield efficient weights with the highest expected returns per unit of risk (Amenc et al., 2011). The optimal weights are calculated as per Eq.20:

$$w^{SR} = \underset{\text{s.t.}}{\mathrm{Max}} \frac{w^T \mu}{\sqrt{w^T \Sigma w}} \qquad (20)$$

$$\sum_{i=1}^{N} w_i = 1,$$

$$w_i \geq 0$$

Where, µ represents the vector of expected returns over the risk-free rate and ∑ is the covariance matrix for returns.

Diversified Multi-Strategy

Amenc et al. (2012b) demonstrated that alternative-weighted indices outperformed cap-weighted indices over the long run. However, no single allocation approach is better than any other because they all perform differently in various market scenarios. In essence, this can be explained by the fact that the models use different strategies (e.g., by enhancing performance, minimizing volatility, and focusing on low correlations) to attain risk-adjusted outperformance. Therefore, in order to diversify strategy-specific risks, an investor should combine several allocation techniques.

Table 2: Summary of Objective wise Methodology used

Objectives	**Sample and Sample Period**	**Techniques/Method**
Objective 1: To examine the weak-form market efficiency of the Indian Stock market	Sample: NSE 500 index Sample Period: October 1999 to December 2022	EMH has been carried out with a battery of tests, including the autocorrelation Test (Ljung and Box), runs test, Bartel test, Variance ratio test, and BDS test. After that, adaptive market hypothesis was tested i.e., the study investigated the evolving weak-form market efficiency using the rolling window approach. Subsequently, a range of linear and non-linear tests, including the variance ratio, autocorrelation, runs, Bartel, and BDS tests, were applied to the rolling returns to analyze the evolving market efficiency.
Objective 2: To explore the linkage Between market Liquidity and efficiency	Sample: Stock Constituents of the NSE 500 index Sample Period: June 2008 to December 2022	Firstly, liquidity is measured using multiple dimensions: depth, tightness, immediacy, breadth, and resiliency. Afterward, the connectedness of market liquidity and efficiency was examined by testing the EMH on the returns of several stocks that have been sorted for market liquidity.
Objective 3: To study the presence of different anomalies in the Indian Stock Market	Sample: Stock Constituents of the NSE 500 index Sample Period: July 1, 2003, to June 30, 2020	The presence of anomalies, including Value effect, Size, Momentum, Investment, Profitability, and Low volatility, were examined for the Indian Stock Market.
Objective 4: To construct and evaluate the performance of alternative equity indexing strategies	Sample: Stock Constituents of the NSE 500 index Sample Period: July 1, 2003, to June 30, 2020	Alternative equity indexing strategies, including Efficient Minimum Variance, Diversified Risk-weighted, Maximum Decorrelation, Maximum Deconcentration, Efficient Maximum Sharpe ratio, and Diversified Multi-Strategy, were tested.

As portrayed by Amenc et al. (2015) and Gonzalez and Thabault (2013), the combination of the various weighting schemes helps to eliminate any remaining model risk. Hence, this study employed the “Diversified Multi-Strategy" approach, which combines equal proportions of the five different weighting schemes (Efficient Minimum Variance, Diversified Risk-weighted, Maximum Decorrelation, Maximum Deconcentration, and Efficient Maximum Sharpe ratio), and thereby diversifying any unrewarded risks and errors in anticipating the parameters.

Chapter 4
Results and Discussion

CHAPTER 4
RESULTS AND DISCUSSION

In this chapter, we go into further detail on the conclusions and results of the statistical analysis that was done to achieve the stated study objectives.

Data Analysis and Findings

Table 3: Preliminary Analysis of Stock Returns

Observations	5868
Mean	0.000507
Median	0.001406
Maximum	0.150340
Minimum	-0.137063
Std. Dev.	0.014364
Skewness	-0.679042
Kurtosis	12.18823
JB Normality	21092.49
Probability	0.000000

Source: Author's findings.

The outcomes of descriptive statistics for the daily returns of the Indian stock market index are shown in Table 3. The initial analysis is presented, including the mean, standard deviation, minimum, maximum, skewness, and kurtosis. It reports the preliminary analysis, namely mean, maximum, standard deviation, minimum, skewness, and kurtosis. Over the course of the examined sample period, the results showed positive mean returns. It is noteworthy to mention that the skewness value was found to be negative, indicating that extreme negative returns typically outweigh extreme positive ones. In particular, this shows that there was an asymmetry in the distribution of the daily index returns. Later, it is noted that the kurtosis value is higher than 3 (a measure of the Leptokurtic distribution), indicating the presence of extreme mean return values and higher peaks. The null hypothesis that the daily returns are normally distributed is rejected by the Jarque–Bera test at a significance level of 1%.

Table 4: Testing of weak-form Market Efficiency (Absolute efficiency approach)

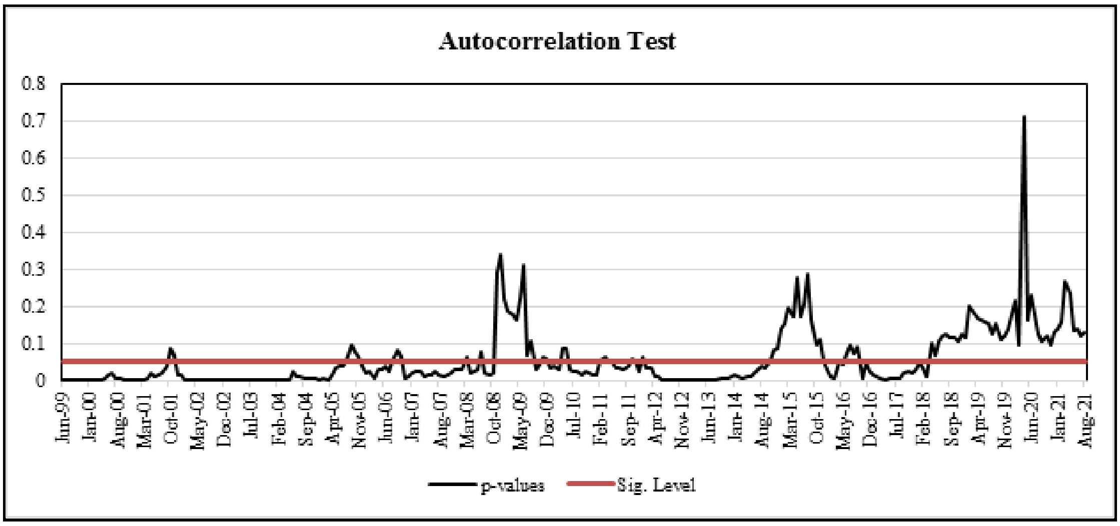
	p-values				
Time Period	**Autocorrelation Test (Ljung-Box)**	**Bartel test**	**Runs test**	**VR Test**	**BDS Test**
1999-2022	0.0000	0.0000	0.0000	0.002	0.0143

Source: Author's findings.

First, the study used the conventional absolute efficiency approach to examine the weak-form market efficiency over the selected time period. This approach uses an absolute, all-or-nothing view of efficiency to determine whether a stock market is efficient or inefficient within a given time frame. Table 4 demonstrates that all of the p-values are significant from the beginning of the sample to December 2022, demonstrating the predictability of returns. Particularly, the significant p-values derived from the outcomes of the linear and non-linear tests showed the predictability of return. In essence, the results of the conventional absolute efficiency tests confirmed that the Indian stock markets are predominantly inefficient. The findings are in line with the previous studies Kulkarni (1978), Chaudhuri (1991), Poshakwale (1996), Pant and Bishnoi (2001), Pandey (2003) and Gupta and Basu (2007), (Mishra, 2009a) and (Mishra, 2009b), Gupta & Siddiqui (2010), Srinivasan (2010), Khan et al. (2011), Harper and Jin (2012), and Malafeyev et al. (2019).

Since prices do not represent random behavior, investors can forecast an upward or downward pattern in the stock prices. In other words, the results observed that the Indian stock market does not adhere to the weak-form market efficiency. Above all, the outcome of absolute efficiency implied that investors can make significant profits by using a disciplined approach to seizing trading opportunities in the Indian stock market.

Testing of weak-form Market Efficiency (Evolving efficiency approach):

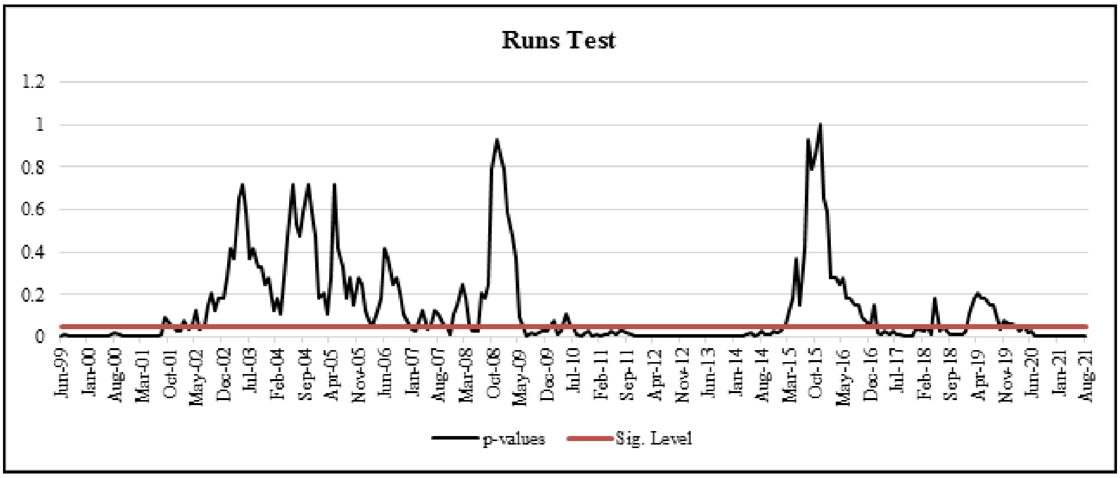


Source: Author's findings.

Figure 8: The evolving behavior of p-values for Autocorrelation test statistic

Figure 8 displays the first-order autocorrelation p-values for the Indian equities market (NSE 500 index) across time. It is evident that the p-values produced by the sample fluctuate over time, with some periods producing statistically significant p-values and others yield relatively high estimates. Almost all of the p-values from the beginning of the sample to October 2008 are significant, indicating the dependency and predictability of stock returns. However, the p-values show a fluctuating pattern of stock returns from November 2008 to December 2015, ranging from statistically significant to insignificant. Moving further, nearly all of the p-values between

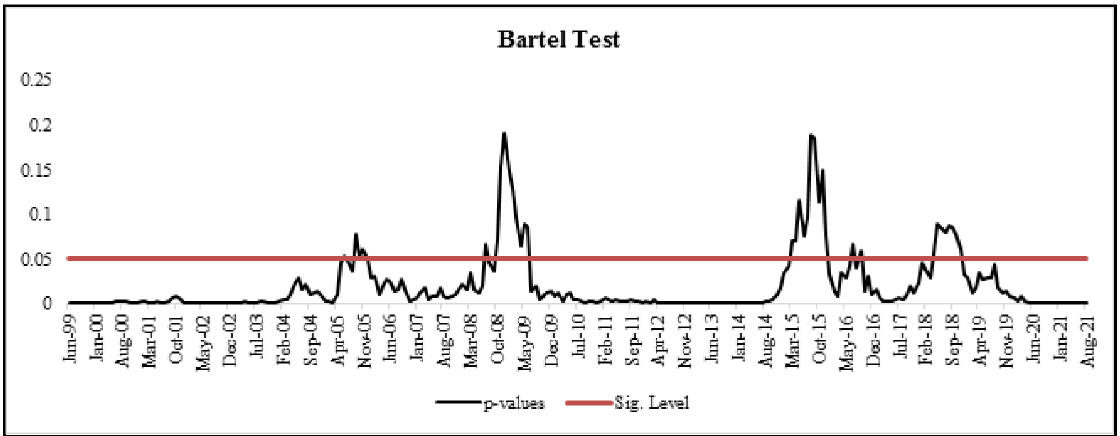
December 2015 and March 2018 are statistically significant, demonstrating the predictability of stock returns. Finally, all of the p-values from March 2018 to the end of the sample are insignificant, indicating that stock returns are unpredictable. The autocorrelation test shows that the Indian equity market is compatible with the AMH, i.e., it exhibits cycles of efficiency and inefficiency.



Source: Author's findings.

Figure 9: The evolving behavior of p-values for Runs test statistic

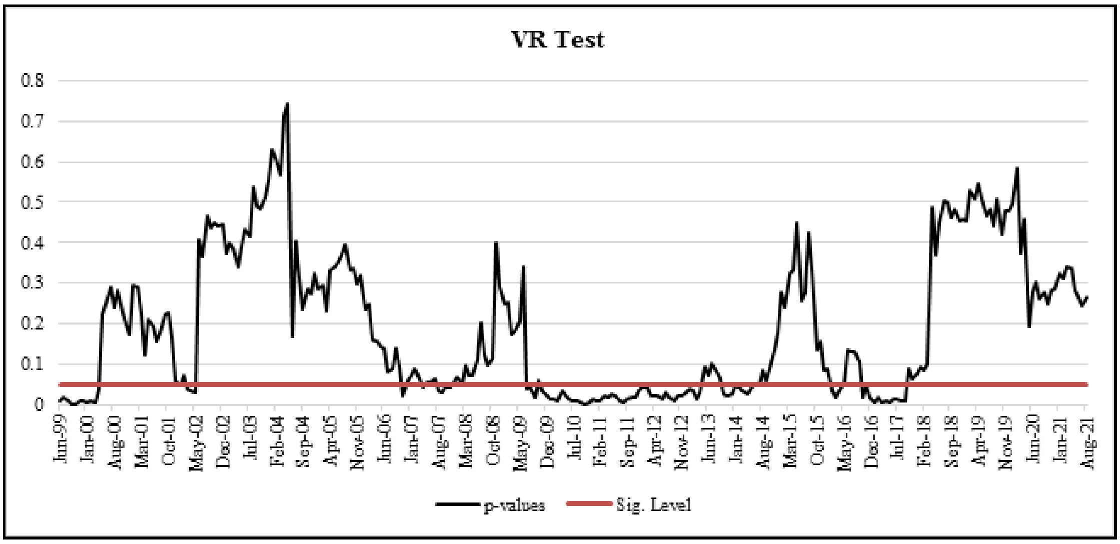
Figure 9 presents the runs test p-value statistics over time, and there is again clear evidence of the time-varying behavior of stock return predictability. Given that all of the p-values are significant, there is evidence of strong predictability from the beginning of the period to March 2002. Nevertheless, almost all of the p-values between March 2002 and June 2009 at the 5% level are insignificant or quite close to being insignificant, signifying the unpredictable nature of stock returns. Further, the p-values are all significant beyond this threshold, indicating that the returns are considered predictable. However, the p-values show a fluctuating pattern of stock returns from January 2015 to February 2020, ranging from statistically significant to insignificant. Lastly, all p-values are statistically significant from February 2020 to the end of the sample period, demonstrating the unpredictable behavior of returns. In essence, there is convincing evidence of evolving nature of the stock return predictability, which is in line with the theory of AMH.



Source: Author's findings.

Figure 10: The evolving behavior of p-values for Bartel test statistic

Figure 10, which displays the Bartel test p-values across time, provides extensive evidence of the time-varying nature of stock return predictability. For the following time periods: June 1999 to August 2005, December 2005 to September 2008, July 2009 to February 2015, January 2016 to March 2018, and December 2018 to the end of the sample, there is strong evidence of predictability. These periods reflect that the market exhibits inefficiency and thus, market players can earn anomalous returns. The remaining periods, on the other hand, demonstrate insignificant outcomes and, hence, the unpredictable character of returns. In essence, the results are compatible with the AMH, as the Bartel test indicates that there have been periods of predictability and unpredictability in the Indian equity market.



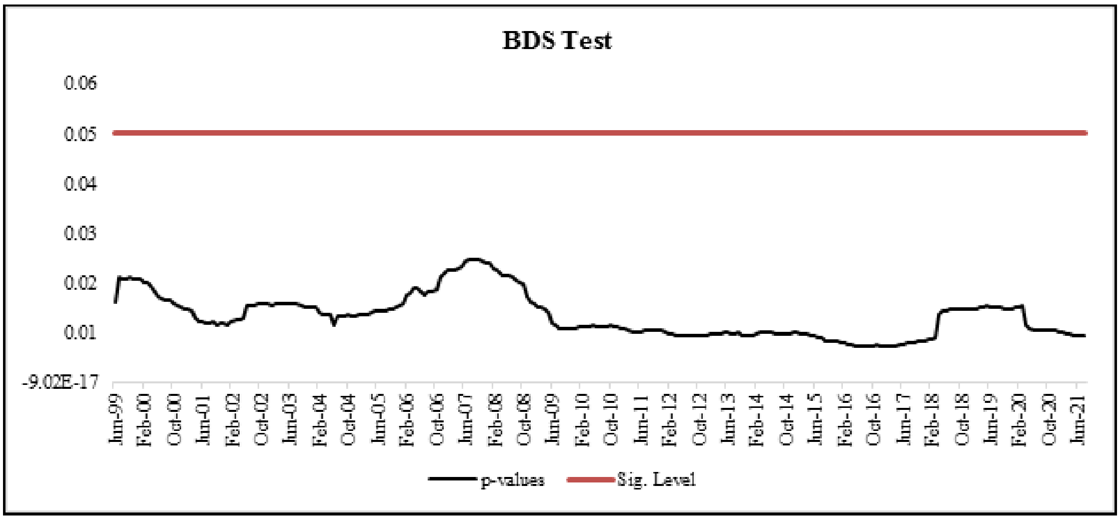
Source: Author's findings.

Figure 11: The evolving behavior of p-values for Variance Ratio test statistic

Figure 11 displays the p-values of variance ratio test for the NSE 500 index, and it is evident that there have been periods of predictability and unpredictability in the Indian stock market. It is noted that the p-values generated by the sample change with time, with some periods producing statistically significant p-values and others generating p-values that are comparatively high. All of the p-values from the beginning of the peirod to April 2000 are significant, demonstrating the predictability of returns. Following this, from May 2000 to June 2009, nearly all of the p-values for the test were insignificant, indicating the independence and unpredictable nature of stock returns.

On the other hand, almost all of the p-values between July 2009 and July 2014 were significant, demonstrating the predictability of the stock returns. Nonetheless, the p-values showed a fluctuating pattern of stock returns from August 2014 to September 2017, alternating between being statistically significant and insignificant. Finally, from September 2017 to the end of the sample, all the p-values were insignificant, representing the unpredictable nature of stock returns. Consequently, as the equity market experiences cycles of predictability and unpredictability, the variance ratio test results are consistent with the AMH. In other words, the current evidence indicates a varying behavior of stock returns across the sample.

According to the findings of the linear test, the Indian stock market fluctuated between periods of efficiency and inefficiency i.e., the results are consistent with the adaptive character of stock returns. This conclusion is in line with the findings of Kim et al. (2011), Alvarez-Ramirez et al. (2012), and Charles et al. (2012).



Source: Author's findings.

Figure 12: The evolving behavior of p-values for BDS test statistic

Figure 12 reports the BDS statistic p-values from the rolling window analysis. The findings of the nonlinear BDS test show a significant existence of nonlinear dependence, which could signify possible return predictability and consequent excess returns. Consequently, the statistical significance of the BDS test p-values is apparent, indicating the weak-form inefficiency of the Indian equity market. In a nutshell the current evidence showing a substantial nonlinear dependence of stock returns across the sample implies that the Indian stock market is still inefficient and has not yet attained efficiency.

There is ample evidence that the efficiency of the Indian equity market varies across time, exhibiting both efficient and inefficient periods. To put it briefly, our research concluded that the AMH framework offers a more comprehensive explanation of emerging market behavior than the EMH.

Table 5: Descriptive Statistics for Liquidity Measures

	AR	**ST**	**CET**	**RQS**	**MEC**
	Breadth	Depth	Immediacy	Tightness	Resiliency
Mean	-7.2704	-6.2067	4.7896	-6.8029	-0.3150
Median	-7.3348	-6.2529	4.7750	-6.8165	-0.3145
Maximum	-4.8878	-4.7372	7.9155	-2.3789	0.5911
Minimum	-8.2106	-10.0260	1.0763	-10.8916	-1.5992
Std. Dev.	0.3713	0.3673	0.6583	0.4162	0.1043
Skewness	1.2216	-0.5656	0.1260	1.9609	-0.6054
Kurtosis	5.6439	9.9782	5.0516	30.9345	13.2512

Source: Author's findings.

Table 5 summarizes the descriptive statistics for the liquidity measurements. Compared to other measures, the log mean values show that CET is greater and AR is lower, indicating that vast volumes of securities may be traded quickly and at a lower price effect. It further shows that the high log mean value of MEC indicates that order imbalances are better corrected throughout the sample. Next, in terms of market depth, the value of ST suggests that the market is deeper, implying that the market has a significant number of orders to keep price equilibrium. Furthermore, it is notable that RQS is higher than AR, indicating higher trading costs for completing a market transaction.

Table 6: Descriptive Statistics of Returns Sorted by Liquidity

Sort by Liquidity		Return Characteristics						
	Group	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**
High liquidity	1st Quintile	0.000283	0.000557	0.15775	-0.15309	0.01139	-0.47535	9.72703
	2nd Quintile	0.000525	0.000686	0.13359	-0.15769	0.01333	-0.89261	17.4276
	3rd Quintile	0.000432	0.000216	0.16149	-0.15406	0.01246	-0.45047	14.9783
Low Liquidity	4th Quintile	0.000506	0.000388	0.14542	-0.01139	0.014992	-0.19428	18.9844
	5th Quintile	0.000580	0.000257	0.15123	-0.12374	0.01724	-0.16110	18.4445

Source: Author's findings.

Table 6 shows the return statistics for the different quintiles, which are divided into five groups depending on the Depth ratio, with group 1 being the most liquid and group 5 being the least liquid. The results observed that, on average, the stock market had positive returns based on the quintiles. Notably, the findings also imply an illiquidity premium, as noted in the highest mean return for the 5th quintile, signifying that equity investors must expect a premium to retain illiquid stocks. However, considering the standard deviation, the 5th quintile has the most extensive volatility, while the 1st quintile has the lowest. The results align with the premise that pricing efficiency is higher in liquid markets with more active traders, resulting in lower volatility.

Table 7 shows that the upper and lower quintile groups have a substantial gap in share turnover (almost 30 percent). Furthermore, AR is smaller in the upper quintile (most liquid), meaning heavily traded equities have less price influence due to their trading consistency.

Table 7: Descriptive statistics for liquidity measures for the Quintiles

	1st Quintile					2nd Quintile					3rd Quintile				
	RQS	CET	ST	AR	MEC	RQS	CET	ST	AR	MEC	RQS	CET	ST	AR	MEC
Mean	-6.891	4.840	-5.359	-7.402	-0.301	-6.878	4.667	-5.866	-7.385	-0.303	-6.804	4.431	-6.118	-7.153	-0.316
Median	-6.851	4.185	-5.460	-7.106	-0.292	-6.704	4.624	-5.919	-7.205	-0.305	-6.918	4.386	-6.174	-7.296	-0.317
Maximum	-2.100	9.006	-3.701	-4.829	0.225	-2.344	8.528	-4.150	-4.942	0.448	-2.398	8.966	-4.418	-4.833	0.640
Minimum	-10.275	1.072	-9.605	-8.086	-1.645	-9.799	1.046	-10.088	-8.195	-1.627	-12.321	0.662	-9.861	-8.549	-1.264
Std. Dev.	0.457	0.767	0.548	0.425	0.136	0.454	0.755	0.412	0.391	0.111	0.546	0.817	0.415	0.434	0.140
Skewness	2.919	0.201	0.267	0.772	-0.517	1.414	0.382	-0.238	0.953	-0.712	1.275	0.485	-0.113	0.798	-0.071
Kurtosis	30.701	4.509	4.192	4.075	5.487	14.772	4.471	9.147	4.865	10.221	25.882	4.748	7.517	4.363	4.670
	4th Quintile					5th Quintile									
	RQS	CET	ST	AR	MEC	RQS	CET	ST	AR	MEC					
Mean	-6.655	4.658	-6.561	-7.242	-0.308	-6.629	4.199	-6.974	-7.051	-0.345					
Median	-6.912	4.598	-6.601	-7.434	-0.344	-6.658	4.762	-7.047	-7.447	-0.302					
Maximum	-2.415	9.055	-4.500	-4.933	0.389	-2.179	9.031	-4.331	-4.768	1.837					
Minimum	-8.332	1.142	-10.385	-8.527	-1.862	-10.202	0.956	-10.147	-8.723	-1.838					
Std. Dev.	0.440	0.812	0.409	0.403	0.129	0.522	0.851	0.492	0.451	0.157					
Skewness	3.149	0.495	-0.503	0.908	-0.572	3.229	0.522	0.259	0.752	1.009					
Kurtosis	23.332	4.501	9.209	4.818	11.275	23.877	4.559	5.218	4.589	23.003					

Notably, the MEC for the top quintiles is particularly high, implying a better correction of order imbalances for highly traded stocks. Furthermore, the upper quintile has a greater CET, indicating speedy flow of order transactions. It is noted that other indicators such as the dimension of tightness suggested that stocks in the lower quintile have higher spreads (as measured by RQS) than those in the upper quintile. This means that trading in low-volume equities is expensive than trading in high-volume ones.

Table 8: Results for Weak-Form of Market Efficiency sorted by Liquidity

Sort by Liquidity		**p- values**				
	Group	**Autocorrelation Test**	**Bartel test**	**Runs test**	**AVR**	**BDS**
High liquidity	1st Quintile	0.374	0.1145	0.179	0.282	0.017*
	2nd Quintile	0.695	0.1498	0.112	0.228	0.015*
	3rd Quintile	0.18	0.033*	0.07	0.039*	0.013*
	4th Quintile	0.04*	0.044*	0.023*	0.042*	0.011*
Low Liquidity	5th Quintile	0.018*	0.029*	0.002*	0.046*	0.012*

Note. * denotes significance at 5% level.
Source: Author's findings.

Table 8 displays the efficiency results for the five different quintiles. Considering the results of quintiles, the p-values of the lowest quintile (with the least liquidity) reject the null hypothesis of randomness in all tests at a 5% significance level. Put another way, the quintiles with the least liquidity diverge the most from market efficiency. However, higher liquidity quintiles exhibit higher average p-values, showing that high-liquid markets are more efficient. There is typically more trading activity in an efficient market because players may quickly modify their investment positions in reaction to new information, which causes prices to reflect the information. The findings are noteworthy because they suggest a linkage between market liquidity and market efficiency, signaling that stronger liquidity is associated with greater efficiency.

Table 9: Absolute Performance Statistics of Anomalies-Based Investment Strategies

Panel A: Value Strategy				
	RP	FW	EW	NSE500
Monthly Return	1.58 (0.04)	1.60 (0.12)	1.90 (1.15)	1.57
Volatility	7.99	9.20	9.07	7.07
Sharpe ratio	0.13 (-0.54)	0.11 (-0.48)	0.15 (0.19)	0.14
Maximum Drawdown	26.78	30.34	29.88	27.11
Downside Risk	4.24	4.83	4.70	3.99
Sortino Ratio	0.24 (-0.54)	0.22 (-0.48)	0.29 (0.76)	0.25

Panel B: Investment Strategy				
	RP	FW	EW	NSE500
Monthly Return	1.71 (0.72)	2.02* (2.09)	2.13* (2.39)	1.57
Volatility	6.85	8.03	8.16	7.07
Sharpe ratio	0.17* (2.12)	0.18* (3.16)	0.19* (3.35)	0.14
Maximum Drawdown	22.62	27.41	26.98	27.11
Downside Risk	3.59	4.16	4.19	3.99
Sortino Ratio	0.32* (2.35)	0.35* (7.89)	0.38* (8.72)	0.25

Panel C: Profitability Strategy				
	RP	FW	EW	NSE500
Monthly Return	2.53* (5.41)	3.04* (9.50)	3.13* (9.49)	1.57
Volatility	5.92	6.80	7.03	7.07
Sharpe ratio	0.33* (2.74)	0.36* (5.37)	0.37* (6.57)	0.14
Maximum Drawdown	19.53	22.86	23.07	27.11
Downside Risk	3.06	3.44	3.52	3.99
Sortino Ratio	0.64* (5.63)	0.72* (11.46)	0.73* (13.70)	0.25

Panel D: Size Strategy				
	RP	FW	EW	NSE500
Monthly Return	2.30* (2.62)	2.86* (3.88)	3.01* (4.33)	1.57
Volatility	7.89	9.05	9.12	7.07
Sharpe ratio	0.22* (10.67)	0.25* (3.35)	0.27* (4.06)	0.14
Maximum Drawdown	24.49	28.86	28.56	27.11
Downside Risk	3.97	4.43	4.42	3.99
Sortino Ratio	0.44* (12.46)	0.52* (8.23)	0.55* (9.36)	0.25

Panel E: Momentum Strategy				
	RP	FW	EW	NSE500
Monthly Return	2.44* (4.05)	2.93* (6.08)	2.98* (6.05)	1.57
Volatility	6.58	7.59	7.79	7.07
Sharpe ratio	0.29* (3.19)	0.31* (11.4)	0.31* (15.54)	0.14
Maximum Drawdown	22.10	25.63	26.61	27.11
Downside Risk	3.36	3.79	3.86	3.99
Sortino Ratio	0.56* (6.60)	0.62* (14.82)	0.63* (15.22)	0.25

Panel F: Low Volatility Strategy				
	RP	FW	EW	NSE500
Monthly Return	1.70* (2.13)	1.89* (2.39)	1.94* (3.81)	1.57
Volatility	5.33	5.87	6.11	7.07
Sharpe ratio	0.21* (2.09)	0.23* (2.42)	0.24* (2.79)	0.14
Maximum Drawdown	18.51	20.99	21.37	27.11
Downside Risk	2.88	3.14	3.24	3.99
Sortino Ratio	0.40* (2.21)	0.42* (2.68)	0.43* (3.22)	0.25

Notes: Author's Calculation based on monthly total returns from July 1, 2003, to June 30, 2020. The cap-weighted index is represented by the Indian stock market index. The risk-free rate is calculated using the yield on 91 days Treasury bills. The computed results are reported in percentages except for Sharpe and Sortino ratios. The t-statistics are presented in parentheses, and (*) values are significant at the 5% level. RP: Risk Parity; FW: Factor Weighting; EW: Equal Weighting.

Source: Author's findings.

Table 9 summarizes the presence of different market anomalies over the study period. Notably, the different anomaly-based investment strategies have led to statistically significant higher returns and superior Sharpe and Sortino ratios than the NSE 500 index. However, we have found no robust value effect in recent years. This result aligns with Hillard and Zhang (2015) and Hu et al. (2019). Particularly, profitability and low volatility are optimal strategies with higher returns and lower volatility than the market index. It is also evident that the Equal Weighted (EW) portfolio delivered comparatively good risk-adjusted performance, i.e., it beats the other portfolios in terms of monthly return, Sharpe ratio, and Sortino ratio. These results where EW portfolios outperformed are consistent with the previous studies (DeMiguel et al., 2009; Malladi and Fabozzi, 2017 and, more recently, Bermejo et al., 2021).

Meanwhile, the Risk Parity (RP) portfolios hold the lowest volatility, i.e., being consistent with the rationale of risk-minimization strategies (Chaves et al., 2011). At the same time, for the other attributes, say, Maximum Drawdown and Downside risk, RP portfolios are clearly at an advantage compared to other stock weighting schemes. Typically, Panel C, E, and F of Table 8 show that profitability, momentum, and low volatility have maximum drawdown generally around 18.51% to 26.61% as compared to 27.11% for the NSE 500 and downside risk ranging between 2.88% to 3.86% as contrasted to 3.99% for the market index. These attributes show lower levels of underperformance for these strategies than the traditional market index.

Table 10: Relative Performance Measures of Anomalies-Based Investment Strategies

Panel A: Value Strategy	RP	FW	EW
Relative Return	0.01	0.03	0.33
Tracking Error	3.13	3.87	3.81
Information Ratio	0.003	0.008	0.09
Maximum Relative Drawdown	12.17	10.44	10.26
Extreme Relative Returns (5^{th} %ile)	-4.61	-5.28	-5.10
Extreme Tracking Error (95^{th} %ile)	4.84	5.84	6.16

Panel B: Investment Strategy	RP	FW	EW
Relative Return	0.14	0.45	0.56
Tracking Error	2.64	2.91	3.15
Information Ratio	0.05	0.15	0.18
Maximum Relative Drawdown	12.95	10.99	11.47
Extreme Relative Returns (5^{th} %ile)	-3.65	-3.96	-4.30
Extreme Tracking Error (95^{th} %ile)	4.75	5.48	6.10

Panel C: Profitability Strategy	RP	FW	EW
Relative Return	0.96	1.47	1.56
Tracking Error	2.38	2.08	2.17
Information Ratio	0.40	0.71	0.72
Maximum Relative Drawdown	9.17	5.39	5.30
Extreme Relative Returns (5^{th} %ile)	-2.61	-1.83	-1.76
Extreme Tracking Error (95^{th} %ile)	4.62	5.03	5.27

Panel D: Size Strategy	RP	FW	EW
Relative Return	0.73	1.29	1.44
Tracking Error	3.73	4.46	4.45
Information Ratio	0.20	0.29	0.32
Maximum Relative Drawdown	12.17	11.19	9.42
Extreme Relative Returns (5^{th} %ile)	-4.58	-4.60	-4.59
Extreme Tracking Error (95^{th} %ile)	7.46	9.68	10.02

Panel E: Momentum Strategy	RP	FW	EW
Relative Return	0.87	1.36	1.41
Tracking Error	2.89	3.00	3.13
Information Ratio	0.30	0.45	0.45
Maximum Relative Drawdown	9.35	7.41	8.41
Extreme Relative Returns (5^{th} %ile)	-3.62	-3.15	-3.39
Extreme Tracking Error (95^{th} %ile)	5.26	6.20	6.33

Panel F: Low Volatility Strategy	RP	FW	EW
Relative Return	0.13	0.32	0.37
Tracking Error	2.73	2.35	2.36
Information Ratio	0.05	0.14	0.16
Maximum Relative Drawdown	11.66	11.22	10.67
Extreme Relative Returns (5^{th} %ile)	-3.97	-3.60	-3.43
Extreme Tracking Error (95^{th} %ile)	3.88	3.43	3.60

Notes: Relative returns are the excess return of the factor strategy over the benchmark (S&P BSE 500 index). All results are reported per month and in percentages except for the Information ratio.
Source: Author's findings.

The results presented in Table 10 measure the relative risk-return performance of these diverse portfolios. An examination of relative performance shows that the anomaly-based strategies outperformed the standard index, with monthly excess returns ranging from 0.01% and 1.56%. It is noted that the EW portfolios generated the highest excess returns, which is not surprising as Table 9 displays an identical pattern for the absolute returns. From Table 10, we find that EW portfolios also lead to superior risk-adjusted performance, i.e., Information Ratio.

Furthermore, it is interesting to examine the tracking error (the volatility of excess returns) for the anomaly based strategies. Particularly, the RP weighted portfolios have the lowest tracking error to the NSE 500 in four out of 6 cases. On the other hand, the FW portfolios deliver a lower tracking error in profitability and low volatility. Finally, Panel C of Table 10 displays that the profitability strategy generates the highest relative return and is accompanied by the lowest tracking error, resulting in the highest information ratio. However, value strategy (Table 10, Panel A) gives the lowest excess return compared to other strategies.

Besides examining the attributes of return and volatility for different portfolios, our approach includes other parameters that are also valuable for analyzing the consistency and robustness of the anomaly based investment strategies. Furthermore, previous literature (Fuller & Goldstein, 2011; Amenc et al., 2014) suggested separating bull and bear phases when analyzing conditional performance. In light of this, we used the method proposed by Qian (2015) to evaluate a portfolio's ability to capture upside returns while limiting downside risk. As a result, we computed upside and downside participation ratios to evaluate whether the performance of these strategies is persistent across different market environments. Following that, we calculated the participation advantage and average participation. Interestingly, participation advantage measures the difference between the upside and downside participation ratios and demonstrates the strategy's effectiveness in creating value over the entire market cycle.

Table 11: Performance of Investment Strategies under Bullish and Bearish Market Conditions

Panel A: Value Strategy			
	RP	FW	EW
Upside Participation	1.06	1.20	1.27
Downside Participation	1.27	1.48	1.36
Average Participation	1.17	1.34	1.32
Participation Advantage	-0.21	-0.28	-0.09

Panel B: Investment Strategy			
	RP	FW	EW
Upside Participation	1.04	1.22	1.26
Downside Participation	0.96	1.10	1.10
Average Participation	1.00	1.16	1.18
Participation Advantage	0.08	0.12	0.16

Panel C: Profitability Strategy			
	RP	FW	EW
Upside Participation	1.20	1.41	1.42
Downside Participation	0.53	0.53	0.54
Average Participation	0.87	0.97	0.98
Participation Advantage	0.67	0.88	0.88

Panel D: Size Strategy			
	RP	FW	EW
Upside Participation	1.30	1.54	1.59
Downside Participation	1.03	1.08	1.06
Average Participation	1.17	1.31	1.33
Participation Advantage	0.27	0.46	0.53

Panel E: Momentum Strategy			
	RP	FW	EW
Upside Participation	1.23	1.44	1.47
Downside Participation	0.68	0.73	0.75
Average Participation	0.96	1.09	1.11
Participation Advantage	0.55	0.71	0.72

Panel F: Low Volatility Strategy			
	RP	FW	EW
Upside Participation	0.93	1.02	1.06
Downside Participation	0.67	0.75	0.78
Average Participation	0.80	0.89	0.92
Participation Advantage	0.26	0.27	0.28

Note: In upside participation, the bull market corresponds to the positive market returns. While in downside participation, months with negative returns comprise bear markets.
Source: Author's findings.

A strategy with a positive participation advantage is considered better than one with negative participation because a strategy with a positive advantage gives "upside participation and downside protection" (Qian, 2015). In comparison, the average participation indicates whether the portfolio is cyclical or defensive. A portfolio can be classified as cyclical when its accumulating benefits arise when the market is up. Conversely, the strategy accruing substantial benefits when the market is down is considered a defensive one. The convention is that if the average participation value is greater than one, the strategy is cyclical, and if that value is less than one, it turns out to be defensive. However, with an average value of 1, that portfolio is termed neutral, i.e., neither cyclical nor defensive (Sorensen et al., 2018).

To test this empirically, we evaluated the performance patterns of these strategies over different market cycles (Table 11). The outcome illustrates that profitability, momentum, and size strategies show relatively high participation advantages and provide more opportunities over the cycle. In comparison, other strategies substantially have low participation advantages. Moreover, according to the average participation, low volatility and profitability strategies are more defensive and pay off more when the market is down. From the results obtained, the EW approach is progressively preferred as it has the highest participation advantage and thus gives the maximum upside participation and downside protection. As a result, the present study shows ample evidence that these strategies are consistent, robust, and outperforming, irrespective of the market conditions. The findings of the study are aligned with the results of Amenc et al. (2014) and Sorensen et al. (2018).

Table 12: Different measures of Anomaly Based Investment Strategies

Panel A: Value Strategy			
	RP	FW	EW
Alpha (%)	0.28	0.43*	0.49*
Market Beta	0.85*	0.89*	0.89*
SMB Beta	0.28*	0.21*	0.29*
HML Beta	0.25*	0.34*	0.29*
MOM Beta	0.02	0.02	0.02
LVOL Beta	-0.08*	-0.20*	-0.19*
INV Beta	0.07	0.10	0.07
PROF Beta	-0.06	-0.08	-0.06
R-Squared (%)	96.23	96.97	96.93
Factor Intensity	0.48	0.39	0.42
Relative Return/Factor Intensity (%)	0.02	0.08	0.79

Panel B: Investment Strategy			
	RP	FW	EW
Alpha (%)	0.50*	0.67*	0.70*
Market Beta	0.84*	0.92*	0.91*
SMB Beta	0.31*	0.27*	0.32*
HML Beta	0.04	0.04	0.06
MOM Beta	0.02	0.01	0.02
LVOL Beta	0.02	-0.09*	-0.10*
INV Beta	0.28*	0.35*	0.35*
PROF Beta	-0.05	-0.06	-0.05
R-Squared (%)	95.93	96.63	96.74
Factor Intensity	0.62	0.52	0.60
Relative Return/Factor Intensity (%)	0.23	0.87	0.93

Panel C: Profitability Strategy			
	RP	FW	EW
Alpha (%)	0.61*	0.70*	0.74*
Market Beta	0.86*	0.94*	0.93*
SMB Beta	0.30*	0.28*	0.31*
HML Beta	0.00	0.01	0.03
MOM Beta	0.04	0.02	0.02
LVOL Beta	0.05	-0.05	-0.07
INV Beta	0.08	0.09	0.05
PROF Beta	0.22*	0.33*	0.30*
R-Squared (%)	94.67	95.57	95.18
Factor Intensity	0.69	0.68	0.64
Relative Return/ Factor Intensity (%)	1.39	2.18	2.44

Panel D: Size Strategy			
	RP	FW	EW
Alpha (%)	0.44*	0.63*	0.68*
Market Beta	0.87*	0.92*	0.92*
SMB Beta	0.63*	0.72*	0.71*
HML Beta	0.08	0.06	0.07
MOM Beta	0.04	0.04	0.05*
LVOL Beta	0.00	-0.09*	-0.12*
INV Beta	0.06	0.05	0.02
PROF Beta	-0.01	-0.03	-0.01
R-Squared (%)	96.16	97.26	97.23
Factor Intensity	0.80	0.75	0.72
Relative Return/ Factor Intensity (%)	0.91	1.72	2.00

Panel E: Momentum Strategy			
	RP	FW	EW
Alpha (%)	0.72*	0.56*	0.60*
Market Beta	0.85*	0.87*	0.89*
SMB Beta	0.35*	0.25*	0.32*
HML Beta	0.11*	-0.06	0.03
MOM Beta	0.33*	0.38*	0.39*
LVOL Beta	0.01	-0.19*	-0.18*
INV Beta	0.07	0.09	0.05
PROF Beta	0.04	-0.05	0.00
R-Squared (%)	95.16	96.06	96.48
Factor Intensity	0.91	0.42	0.61
Relative Return/Factor Intensity (%)	0.96	3.24	2.31

Panel F: Low Volatility Strategy			
	RP	FW	EW
Alpha (%)	0.51*	0.59*	0.63*
Market Beta	0.80*	0.89*	0.89*
SMB Beta	0.29*	0.29*	0.32*
HML Beta	0.00	-0.02	0.00
MOM Beta	0.04*	0.05*	0.03
LVOL Beta	0.18*	0.18*	0.16*
INV Beta	0.02	0.06	0.01
PROF Beta	-0.02	-0.02	-0.04
R-Squared (%)	93.72	94.56	94.45
Factor Intensity	0.51	0.54	0.48
Relative Return/Factor Intensity (%)	0.25	0.59	0.77

Notes: The market factor represents the excess return of the cap-weighted benchmark over the risk-free rate. For the regression part, factor portfolios are created by providing equal weight to the top and bottom three deciles of stocks. Factor intensity is the total of all betas, excluding market beta. Relative return to Factor intensity is a proportion of relative return per unit of factor intensity. The results are based on 204 monthly return observations. (*) value corresponds to the regression coefficients (beta(s) and alpha(s)) that are significant at 5% level.
Source: Author's findings.

Table 12 demonstrates positive and statistically significant monthly alpha ranges from 0.43% to 0.74%. In particular, EW portfolios have the highest monthly alpha, generally around 0.49% to 0.74% in five out of 6 cases, with momentum being the only exception. Table 12 also provides notable insights into the assessment of factor exposures. For example, the SMB varies between 0.21 and 0.72, i.e., positive and substantial across all strategies. Also, exposure to low volatility (LVOL) is significant for the larger part of the strategies; however, the magnitude is not as extraordinary as its worth in terms of the size factor.

Moreover, our analysis extends the outcome for other strategies as well. For example, the investment strategy leads to significant INV factor loadings for RP, FW, and EW as 0.28, 0.35, and 0.35, respectively. Besides, the high profitability strategy has a significant PROF beta of 0.22, 0.33, and 0.30 for the three weighting schemes. In this way, it shows sufficient evidence of different exposures for the anomaly-based investment strategies.

Finally, the study looked at the Relative Return to factor intensity statistics, which depicts how efficiently the factor intensity is employed (Amenc et al., 2017). Mainly, EW portfolios have the highest Relative return to factor intensity for the strategies, with momentum being the exception. This highest ratio infers that the EW portfolios efficiently delivered their factor intensity. Conversely, the RP portfolios have the lowest Relative return to factor intensity, indicating that they cannot efficiently bring their factor exposure.

Table 13: Performance statistics of optimization-based strategies contrasted to Cap-weighted benchmark

	Efficient Minimum Variance	**Diversified Risk-Weighted**	**Maximum Decorrelation**	**Maximum Deconcentration**	**Efficient Maximum Sharpe ratio**	**Diversified Multi-Strategy**	**Cap-weighted**
Monthly Return (%)	2.08	1.85	2.86	1.91	4.05	2.55	1.08
Volatility (%)	4.87	7.08	6.77	7.54	9.03	6.42	6.97
Sharpe ratio	0.31	0.18	0.34	0.18	0.39	0.31	0.07
Maximum Drawdown (%)	-16.65	-24.94	-21.88	-26.08	-17.41	-20.65	-27.11
Downside Risk (%)	2.43	3.85	3.17	4.08	3.45	3.29	4.25
Sortino Ratio	0.62	0.33	0.72	0.33	1.01	0.60	0.12
Relative Return (%)	1.00	0.77	1.78	0.83	2.97	1.47	-
Tracking Error (%)	4.60	2.61	4.68	2.83	7.63	3.59	-
Information Ratio	0.22	0.30	0.38	0.29	0.39	0.41	-

Source: Author's findings.

Table 13 provides performance statistics for all the optimization-based strategies as compared to the conventional cap-weighted stock index. The findings show the optimistic outcome that all the optimized portfolios have resulted in higher monthly returns ranging from 1.85% (Diversified Risk-weighted) to 4.05% (Efficient Maximum Sharpe ratio) as compared to 1.08 % for the standard cap-weighted index. These strategies also have substantially greater Sharpe and Sortino ratios than the cap-weighted benchmark. Therefore, this analysis further suggests that all the strategies show better risk-adjusted performance. Another interesting result is that the optimized portfolios do not increase the overall drawdown levels as much as the cap-weighted indices.

A closer analysis unveils that the Efficient Minimum Variance generates the least volatility among all the strategies; it has a volatility of 4.87% compared to 6.97% for the cap-weighted index. Furthermore, when it comes to the other attributes, such as Maximum Drawdown and Downside risk, this strategy clearly has an advantage over the other risk-efficient solutions.

Table 14: Time-Varying Existence of different strategies: A Sub-Period Approach

	Efficient Minimum Variance	Diversified Risk-Weighted	Maximum Decorrelation	Maximum Deconcentration	Efficient Maximum Sharpe ratio	Diversified Multi-Strategy	Cap-weighted
Monthly Return (%)							
April 2004-March 2008	3.20	3.08	4.83	3.30	8.26	4.53	2.41
April 2008-March 2012	2.52	1.89	3.41	1.89	3.13	2.57	0.64
April 2012-March 2016	1.90	1.77	2.34	1.82	3.09	2.19	0.96
April 2016-March 2020	0.71	0.65	0.85	0.64	1.74	0.91	0.32
Monthly Excess Return (%)							
April 2004-March 2008	0.79	0.67	2.42	0.89	5.85	2.12	-
April 2008-March 2012	1.88	1.25	2.77	1.25	2.49	1.93	-
April 2012-March 2016	0.94	0.81	1.38	0.86	2.13	1.23	-
April 2016-March 2020	0.39	0.33	0.53	0.32	1.42	0.59	-
Tracking Error (%)							
April 2004-March 2008	5.26	3.17	6.74	3.42	11.84	4.87	-
April 2008-March 2012	6.03	2.26	4.80	2.45	7.09	3.77	-
April 2012-March 2016	2.90	2.32	2.91	2.57	4.45	2.50	-
April 2016-March 2020	3.51	2.60	2.97	2.79	3.78	2.57	-
Information Ratio							
April 2004-March 2008	0.15	0.21	0.36	0.26	0.49	0.44	-
April 2008-March 2012	0.31	0.55	0.58	0.51	0.35	0.51	-
April 2012-March 2016	0.32	0.35	0.47	0.33	0.48	0.49	-
April 2016-March 2020	0.11	0.13	0.18	0.11	0.38	0.23	-

Note: A four-year sub-period is used for the analysis, and the calculated results are expressed as percentages except for the Information ratio.
Source: Author's findings.

The findings presented in Table 13 also assess the relative performance of these indexing strategies. This analysis reveals that all alternative indexing methods are superior to the conventional index, with monthly relative returns ranging between 0.77% and 2.97%. Another significant feature of Table 13 is that the Diversified Multi-strategy leads to the highest risk-adjusted performance, i.e., Information Ratio. In this way, the results suggest that investors can diversify the risk relevant to a specific single strategy by allocating it as a diversified multi-strategy index.

In order to comprehend the performance of alternative equity indices under diverse market situations, practitioners employ sub-period analysis to capture the time-varying behavior of distinct strategies. In other words, the study used additional robustness checks by subdividing the study period into four windows. Prominently, this analysis allows different market participants to base their investment decisions on numerous economic scenarios.

Table 14 shows the performance for different sub-periods and offers a clear picture of the time-varying existence of these strategies. During the first period (April 1, 2004-March 31, 2008), the Efficient Maximum Sharpe ratio strategy had the highest excess return and information ratio. During the second period (April 1, 2008-March 31, 2012) and third period (April 1, 2012-March 31, 2016), the maximum decorrelation strategy and Diversified multi-strategy exhibited higher information ratios; however, the maximum efficient Sharpe ratio strategy is not far behind. Further, the result suggested that the maximum Sharpe ratio strategy again dominated the last period (April 1, 2016- March 31, 2020).

A closer inspection reveals that alternative weighting strategies have shown outperformance even for the relatively shorter time frame. The sub-sample analysis thus provides evidence of the time-varying existence of these strategies and, therefore, allows various investment groups to make an investment decision based on different economic circumstances.

Various authors, such as Amenc et al. (2015, 2018) and, more recently, Cai et al. (2018), have proposed to separate the bull and bear market periods for assessing conditional performance. To evaluate this, Table 15 presents the average risk and return statistics over two different sets of periods. The first set comprises the performance of bull markets, and the second set consists of the performance of bear markets.

Table 15: Conditional performance of different strategies in Bull and Bear Market regimes

	Efficient Minimum Variance	Diversified Risk-Weighted	Maximum Decorrelation	Maximum Deconcentration	Efficient Maximum Sharpe ratio	Diversified Multi-Strategy	Cap-weighted
Bull Market							
Monthly Returns (%)	3.75	4.48	5.33	4.71	7.06	5.07	3.48
Monthly volatility (%)	4.61	6.50	6.70	6.95	11.16	5.98	5.39
Sharpe ratio	0.69	0.60	0.71	0.60	0.58	0.75	0.54
Information Ratio	0.06	0.35	0.34	0.39	0.35	0.43	-
Bear Market							
Monthly Returns (%)	-0.52	-2.27	-1.00	-2.45	-0.64	-1.37	-2.66
Monthly volatility (%)	4.48	4.72	4.90	5.04	6.83	4.90	5.15
Sharpe ratio	-0.24	-0.60	-0.32	-0.60	-0.18	-0.40	-0.63
Information Ratio	0.47	0.14	0.42	0.07	0.41	0.37	-

Note: The bull markets are composed of the quarterly period with positive market returns. In contrast, negative quarter returns characterize bear markets.
Source: Author's findings.

The results of Table 15 demonstrated that all the optimized strategies have resulted in superior performance for both market conditions. The findings are backed by the fact that in bull markets, all the strategies have a superior outperformance (for instance, the Sharpe ratio ranging from 0.58 to 0.75 vs. 0.54 for the cap-weighted approach). Meanwhile, in bear markets, it varies from -0.18 to -0.60 as opposed to -0.63 for the cap-weighted benchmark; thus, the traditional cap-weighted index exhibits a more significant decline in bear markets.

Table 15 also suggested that the Diversified Multi-strategy is outperforming in the bull market both in terms of absolute and relative performance, i.e., Sharpe ratio and Information ratio. In contrast, the Maximum Sharpe ratio strategy tends to add more value in bear markets, further showing its more stable outperformance than the other strategies. This analysis holds particular significance for investors who monitor portfolio activity in different market conditions and want to know how this behavior affects the performance of their portfolio.

Table 16 shows that the GLR (Goetzmann et al., 2005) estimate varies from 24.39% to 34.76% for all the alternative indexing strategies compared to 41.33% for the traditional market index. This higher GLR indicates that the conventional benchmark accounts for a high correlation among its constituents, implying that the traditional market index is not well diversified. The analysis in Table 16 is also notable for depicting the decomposition of two types of active risk: factor risk and idiosyncratic risk. Factor risk is the square root of the product of R^2 (i.e., % of Risk Explained by Factor Exposure) and TE^2 (Tracking error squared). In contrast, the idiosyncratic risk is the standard deviation of residuals.

Table 16: Measures of Diversification and Active Risk

	Efficient Minimum Variance	**Diversified Risk-Weighted**	**Maximum Decorrelation**	**Maximum Deconcentration**	**Efficient Maximum Sharpe ratio**	**Diversified Multi-Strategy**
GLR Measure (%)	24.92	34.17	24.39	34.76	33.95	24.69
% of Risk Explained By Factor Exposure	72.20	94.85	76.09	95.26	44.81	84.76
Factor Risk (%)	3.91	2.54	4.08	2.76	5.11	3.31
Idiosyncratic risk (%)	2.58	1.61	3.33	1.65	6.72	2.30
Residual Sharpe ratio	0.25	0.26	0.24	0.25	0.12	0.27

Note: The GLR estimate is the ratio of the portfolio's overall variance to its stock constituents' weighted variance.
Source: Author's findings.

Furthermore, the results depict that the Diversified Risk-weighted strategy has the lowest factor and idiosyncratic risk. It is explained by the fact that this strategy adjusts for volatility and thereby removes the risk concentration. Also, it is noted that Diversified Multi-Strategy has the highest residual Sharpe ratio (i.e., alpha return to idiosyncratic risk) and, therefore, prompts to have the superior idiosyncratic risk-adjusted performance.

Chapter 5
Conclusion

CHAPTER 5
CONCLUSION

The fundamental idea of the efficient market hypothesis is that prices will exhibit a random walk behavior in an efficient stock market, and reflecting their inherent values. An essential requirement for the successful functioning of financial markets is their capacity to accurately and quickly reflect all the available information. On the other hand, if there is inefficiency in the equity markets, investors might receive excess returns. Investors have the opportunity to benefit from arbitrage opportunities in an inefficient market. However, efficiency levels can be raised through improved trading technology, more active investing strategies, improved information flow, and sound regulatory bodies. This will guarantee that investors get risk-adjusted returns and companies get a fair price for their securities. In particular, the ability to diversify risks, hedging strategies, and appropriate portfolio allocation are the elements that have contributed to more substantial economic development.

In contrast to investors in developed markets, emerging market investors are subject to more risk. However, an increment in risk exposure prompts more chances for proficient investors in developing countries. Several differences between developed and emerging economies have been noted in earlier research by Salomons and Grootveld (2003), Kohers et al. (2006), and Chen (2018). These differences include the evolution of the capital market, stock market integration, international diversification, and regulatory frameworks.

Researchers have studied the theory of market efficiency for decades, but they have not yet reached a consensus. Particularly, previous studies and research utilized conventional to advance models for examining the weak-form market efficiency. As one of the most significant elements of emerging economies, we investigated the weak-form market efficiency for the Indian Equity market. The study used both absolute and evolving approaches to analyze weak-form market efficiency. However, the primary drawback of the absolute efficiency tests is that it only evaluates efficiency in a static sense, and ignoring the potential for future fluctuations in return predictability. Particularly, the study examined the predictability of stock returns using linear tests, including the runs test, variance ratio test, autocorrelation test, and Bartel test. Furthermore, the BDS test was employed to determine the possible nonlinearity of the return series. Subsequently, the study tested adaptive market hypothesis using the rolling window technique, yielding several significant insights and making it possible to look into how efficiency changes in Indian equity markets. In other words, the study employed linear and nonlinear tests on moving windows to examine the evolving market efficiency.

The results of the conventional absolute efficiency tests confirmed that the Indian stock markets are predominantly inefficient. Both the linear and non-linear tests yielded significant p-values, ensuring the predictability of return. After that, the evolving market efficiency was investigated for the Indian Equity market. The findings of the rolling linear tests revealed a cyclical pattern that suggested the Indian equity market switched between phases of efficiency and inefficiency. There is ample evidence that the efficiency of the Indian equity market varies across time, encompassing both efficient and inefficient phases. However, the results derived from the nonlinear test (BDS) indicate a noteworthy presence of nonlinear dependency, suggesting the possibility of return predictability and ensuing excess returns. In a nutshell, the findings of the research suggested that AMH framework offers a more comprehensive explanation of emerging market behavior than the EMH.

Secondly, the study tested the multi-dimensions of market liquidity, including tightness, immediacy, breadth, depth, and resiliency. The results of the tightness dimension suggest that there are greater trading expenses in the market when it comes to carrying out a market transaction. Furthermore, there is a high degree of immediacy and a smaller price impact, as shown by CET and AR, suggesting that substantial volumes of securities are traded quickly and with a lower price impact. The research also examined dimensions of liquidity for various quintiles arranged according to the criteria of market depth. The results show that the top quintile with a deeper market has a lower RQS than the bottom quintile, suggesting that trading high liquidity stocks is less expensive. When taking market breadth into account, the top quintile has lower AR, indicating that actively traded stocks has less price influence because of their consistent trading. The high value of MEC for the upper quintiles indicates that liquid stocks are more able to withstand order mismatches than non-liquid ones. Ultimately, the research observed that the immediacy dimension shows that a greater CET in the upper quartile corresponds to a faster flow of trading orders.

Furthermore, we examined the linkage between market efficiency and market liquidity because prior studies have indicated a lack of conclusive evidence on the interconnectedness between the two (Cajueiro & Tabak 2004; Bariviera 2011). The study used the liquidity based quintiles approach to evaluate the linkage between the liquidity and efficiency dimensions. Particularly, to conduct this analysis, five stock quintiles were formed; with the 1st Quintile (upper quintile) being the most liquid and the 5th Quintile (lower quintile) is being the least liquid. The analysis shows that higher liquidity quintiles exhibit efficiency, overall suggesting that high-liquid markets are more efficient. Above all, it is worth noting that increased liquidity equates to greater efficiency, while lower liquidity equates to inefficiency.

Our third area of investigation concerned the existence of different anomalies in the Indian equity market. The study have investigated several investing approaches based on the pattern of anomalies to confirm their presence, including value, size, momentum, investment, profitability, and low volatility. Specifically, we tested the performance of six different anomalies-based investment strategies. The results indicated that the these investment strategies consistently outperformed the market benchmark in terms of higher returns, superior shape ratio, improved information ratio, lower drawdown, better diversification, and downside protection. According to this research, anomaly-based investing has produced a significant amount of robust outperformance, or a stronger risk-return profile both on an absolute and risk-adjusted basis (Amenc et al., 2014; Sorensen et al., 2018; Bender et al., 2018; Bermejo et al., 2021). In addition, the study offers insightful information about the anomalies and emphasizes that, out of all the strategies examined, the profitability approach has produced the best risk-return profile (greater returns and lower drawdown). Another noteworthy point is that profitability and low volatility are the strategies that account stability and robust results even in bearish market conditions. As a result, it is evident that these anomaly-based strategies are a useful tool for diversifying investment portfolios over a range of market conditions.

Given the fluctuations in the traditional index and the impact of inefficient stock markets, investors are now seeking transparent, rule-based indexes with non-market-cap weighting methods. Put another way, the motivation behind this relatively new approach to stock investing is the inherent shortcomings of conventional market indices, namely their excessive concentration and adverse factor exposures. Alternative equity indexing strategies have been developed as an investment philosophy to produce higher risk-adjusted performance. Researchers in the US and other developed markets have investigated the efficacy of these indexing strategies as they gained popularity in financial markets. However, no previous research has been driven to the best of our knowledge that validates the viability and potential execution of these strategies in the Emerging Indian Equity market.

This study presented a systematic overview of the popular optimization-based risk-efficient solutions including: Efficient minimum variance, Diversified risk-weighted, Maximum Decorrelation, Maximum Deconcentration, Efficient Maximum Sharpe ratio, and Diversified Multi-Strategy, as well as their compositional insights. The analysis concluded that the optimized strategies provide evidence of diversification enhancement and extensive outperformance relative to the standard market index. The results suggested that the tested alternative indexing strategies outperformed the traditional cap-weighted benchmark in terms of superior returns, better diversification, improved shape ratio, lower drawdown, higher information ratio, and downside protection. Overall, the study found that the Maximum Shape ratio strategy offers the highest Sharpe ratio and thereby achieves superior risk/reward performance. Conversely, the minimum-variance index experiences the least amount of volatility.

More specifically, a Diversified Multi-strategy achieved the highest risk-adjusted performance (i.e., information ratio) among all other strategies. In turn, this is what motivates the implementation of the diversified strategy for the investors and other market participants. Moreover, in terms of the Information Ratio, the Diversified Multi-strategy obtained the best results in the bull period, while the Maximum Sharpe ratio strategy obtained the best position in bear markets. The analysis, therefore, demonstrated the consistency, robustness, and time-varying properties of these optimized risk-efficient solutions. Put another way, the findings supported that alternative indexation is a viable investment opportunity compared to the conventional market index. In a nutshell, the study suggested that market participants may consider these alternative indexing strategies, including a blended strategy, which best suits, their risk appetite.

Chapter 6
Implications

CHAPTER 6
IMPLICATIONS

The conclusions of the study have a number of implications for the market participants, including investors, regulators, and other market participants. Initially, the results demonstrated that the Indian stock market was weakly inefficient in its absolute form. However, the Adaptive Markets Hypothesis offers a more practical framework for comprehending risk and return in equities markets. The relevance of adaptability, ongoing learning, and the incorporation of adaptive investment strategies is highlighted by the practical implications of the AMH for equity markets.

The evolving nature of market efficiency offers more significant implications. Lo (2012) asserts that investment strategies must be developed and adjusted in response to shifts in predictability. In other words, opportunities to generate money occasionally arise, and when they do, it makes sense to manage the portfolio actively. According to Lo (2004, 2005), the performance of an investing strategy changes with time, doing well in some market conditions and not working well in others. Thus, it is necessary to have adaptable investing strategies that can swiftly change to market conditions. As long as financial markets remain unstable, the debate over market efficiency will remain a vibrant and evolving field of study with ongoing implications for academics, policymakers, and investors.

The study has several other practical implications, including that emerging economies offer investment opportunities to asset managers, market participants, and investor communities. When there is market turbulence and uncertainty, investors should focus on growing stock markets that have the potential to generate returns. The results of the study may serve as further evidence to policymakers in emerging countries that these markets have seen numerous structural and economic downturns. These findings highlighted the need to address market imperfections to reduce the possibility that investors may exploit them, potentially leading to speculative and manipulative actions by vigilant stock market players. Essentially, more efficient markets would draw less manipulative actions and promote higher investor engagement over time.

India is an emerging country that attracts a wide variety of investors with varying degrees of financial need, i.e., some investors want to see long-term financial growth, while others seek guaranteed monthly returns. In essence, market participants and investors can find it simpler to overcome obstacles and take advantage of opportunities if they adjust their plans in accordance with the changing market conditions. Hence, investors and other market players should exercise prudence while selecting their investment strategies.

Adaptive investing strategies that consider the dynamic character of markets may prove advantageous for investors. Put another way, the dynamic nature of markets implies that investors must be perpetual learners. Mainly, investors ought to review their risk tolerance on a regular basis and should make necessary adjustments to their portfolios. Keeping up with emerging technologies, developments in financial research and market patterns can give one a competitive advantage when it comes to modifying investment plans. In order to better navigate changing market situations, strategies that incorporate insights from machine learning, adaptive risk management, and behavioral finance may prove more successful. Overall, it becomes imperative to implement risk management techniques that are adaptable and sensitive to shifting market conditions.

Moreover, the findings of this study can be advantageous to investors, corporations, and market regulators. Liquidity is crucial component that must be constantly evaluated since it ensures the stability of the market as well as the tradability of securities. Specifically, the focus of the present study is on multidimensional metrics for evaluating liquidity, which will help investors, corporations, and market regulators make appropriate decisions and monitor the market. Overall, the results highlighted the importance of liquidity in guiding business and regulatory policy decisions, especially during periods of market uncertainty.

Further, stock market anomalies have real-world applications for academics, market players and investors. Investing in anomaly-based strategies has the potential to boost risk-adjusted returns for investors. Particularly, opportunities to outperform traditional market indices may arise from strategies such as size, momentum, low-volatility and other anomalies based investments. Owing to the ever-changing nature of financial markets, anomalies are subject to change. In order to combat this, it is imperative for investors, academicians, and market regulators to adjust to evolving market conditions and consistently evaluate the applicability of anomaly-based strategies. Furthermore, it has been noted that information of the particular risks associated with anomalies is necessary for effective risk management.

Apart from offering prospects for investors, these strategies also encourage theoretical and scientific research and compel market regulators to adopt preemptive actions to preserve the integrity and effectiveness of the market system. In other words, protecting investors from dishonest practices or market distortions is a major responsibility of regulators. Above all, regulators can put policies in place that improve investor protection by having a deeper comprehension of the significance of anomalies. In essence, these abnormalities must be recognized and comprehended in order to support the ongoing growth of the financial markets and assist in making informed investment decisions.

Alternative equity indexing has become an increasingly valuable investment strategy for practitioners due to its flexibility and applicability in enhancing the construction framework of the portfolio. Continuous growth has paved the way for asset owners and investment managers to improve the risk-return profile of their investment strategies. Overall, it is a significant advancement in the investing field, and various considerations are driving its widespread acceptance. Foremost, implementing optimization-based strategies significantly improves the diversification benefits in a portfolio. A growing number of institutions and index providers used a systematic approach to allocate a portion of their portfolios to alternative equity investing to achieve better returns over longer periods.

Second, from the perspective of the investment process, this novel approach strives to incorporate the most appealing aspects of both active and passive investing. These strategies often seek to capture the factor exposures (i.e. sources of excess returns) that active managers employ to outperform the market. However, these strategies are now delivered in index-like approaches, similar to passive investing, to provide transparency and cost-efficiency. In this way, these products provide exposure to various risk factors at a low cost. Third, by implementing these alternative indexing strategies, various portfolio analysts and fund managers serve the needs of their clients in terms of more diversified investments, less volatile strategies, their objective of return enhancement, and other benefits.

Furthermore, the analysis has intense implications for asset managers, researchers, and groups of investors who are highly involved in alternative indexing investments. The results of the study supported regulators, fund firms, stock analysts, money managers, investors, and other market participants by providing alternative investments, such as alternative index funds, ETFs, and additional diversified funds, to potentially boost their returns. The ideology of alternative indexing provides entrancing opportunities. Thus, in line with the idea, it continues to rise in popularity, but despite this, investors should understand the concept of these indices, know the costs related to this investment, and vigilantly assess which investment style is better allied with their investing values and objectives.

Chapter 7

Limitation and Scope for Future Research

CHAPTER 7

LIMITATION AND SCOPE FOR FUTURE RESEARCH

Even though the study generates consistent and significant results, it has a few limitations as well. This current study primarily focuses on a single emerging economy, i.e., the Indian market, which might limit the ability to generalize the results to other economies. However, economies with similar structural frameworks and peculiarities may consider the outcomes and implement these strategies. It may be helpful to broaden the focus of the EMH research to cover global markets and a variety of asset classes in order to obtain more in-depth understanding. Analyzing the differences in efficiency across different asset types and geographical locations may yield more information. In other words, extending the research to include more countries with parallel structural dynamics would be beneficial.

Furthermore, policymakers and investment managers might benefit from more research on the causes of market inefficiencies and how they affect the market returns in the developing stock markets. One interesting direction to explore could be the use of network analysis to the study of how market participants are connected to the information diffusion in adaptive markets. This may further shed light on how adaptive behavior propagates throughout the financial system.

Moreover, this research is limited to the equity market and does not cover the other asset classes. Consider the following, the different asset classes say bond and commodity markets, differ from the equity market in terms of instruments, structure, regulatory framework, factor exposures, and market participants. Thus, it is very crucial to understand the dynamics of each asset class and then execute these strategies accordingly. Consequently, for future studies, the implementation of alternative indexing in other asset classes and among different emergent markets may be one field of study. For instance, investigate the criteria of alternative indexing in bond and commodity markets.

Another field of research could be a comparative study of alternative indexing among developed and developing nations. Besides this, comparing top-down and bottom-up approaches for various multifactor portfolios is strongly encouraged to be investigated. New dimensions of alternative investment, such as the consolidation of the ESG (Environmental, Social, and Governance) component with other robust variables, may be an essential and novel parameter for the forthcoming articles.

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Appendix

APPENDIX A

Description of the Measures

Sharpe ratio: It is a ratio of the portfolio's excess return over the risk-free rate to the standard deviation. It is calculated using the formula:

$$\text{Sharpe Ratio} = \frac{R_p - R_F}{\sigma_p} \qquad (A1)$$

Where R_P represents the average return of the portfolio, R_F denotes the risk-free rate, and σ_P stands for the standard deviation of the portfolio.

Sortino ratio: It measures the portfolio's return over the risk-free rate in terms of downside deviation. It is calculated using the following Equation:

$$\text{Sortino Ratio} = \frac{R_p - R_F}{\sigma_{Downside}} \qquad (A2)$$

Where $\sigma_{Downside}$ is the Standard deviation of negative returns.

Tracking error (active risk): It is the standard deviation of the dispersion of a portfolio's excess return to its benchmark. It is computed using Equation (A3):

$$\text{Tracking Error} = \sigma(R_p - R_B) \qquad (A3)$$

Information ratio: It is a ratio of the portfolio's excess return over the benchmark to its active risk (tracking error). It is calculated using Equation (A4):

$$\text{Information Ratio} = \frac{R_p - R_B}{\text{Tracking Error}} \qquad (A4)$$

Upside participation ratio: It is the portfolio's average return over the benchmark's average return in the period when the benchmark index is positive, i.e., the bullish period.

$$\text{Upside Participation}\left(\mathrm{P}_{+}\right)=\frac{R_S}{R_B}\ ,\ \ R_B>0 \qquad (\text{A5})$$

Where R_s represents the average return of the strategy, R_B denotes the return of the market benchmark.

Downside participation ratio: It measures the portfolio's average return over the benchmark during the period when the benchmark index is negative (i.e., bearish period)

$$\text{Downside Participation}\left(\mathrm{P}_{-}\right)=\frac{R_S}{R_B}\ ,\ \ R_B<0 \qquad (\text{A6})$$

Participation advantage: It measures the difference between the upside and downside participation ratios. It is calculated using Equation (A7):

$$\text{Participation Advantage} = \mathrm{P}_{+} - \mathrm{P}_{-} \qquad (\text{A7})$$

Average Participation: It is calculated as the average of the upside and downside participation ratios. The following formula is used to determine it:

$$\text{Average Participation } = \frac{\mathrm{P}_{+} + \mathrm{P}_{-}}{2} \qquad (\text{A8})$$

Effective number of stocks (ENS): It is a widely used indicator of portfolio concentration and is calculated as the inverse of the total sum of squared portfolio weights, i.e., the Herfindahl index.

$$\text{ENS} = \frac{1}{\sum_{i=1}^{N} w_i^2} \qquad (\text{A9})$$

Where w_i represents the weight of i^{th} stock; n is the number of stocks.

GLR measure: It is the proportion of the portfolio's variance to the total weighted variance of its stock constituents. It is calculated using Equation (A10):

$$\text{GLR Measure} = \frac{Var\left(R_p\right)}{\sum_{i=1}^{N} w_i \times Var\left(R_i\right)} \qquad \text{(A10)}$$

Standardized Factor-scores (S-Scores): Using the CDF (cumulative distribution function), the Z-factor scores are converted into S-scores by normalizing them between 0 and 1.

$$\text{S-Scores } (\text{S}_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z_i} e^{\frac{-x^2}{2}} \, dx \qquad \text{(A11)}$$

List of Publications

LIST OF PUBLICATIONS

- Monga, R., Aggrawal, D., & Singh, J. (2022). Exploring new frontiers in indexing strategies: an optimization-based risk-efficient solution. *International Journal of System Assurance Engineering and Management*, *13*(Suppl 2), 853-865. (Scopus Indexed, ESCI, IF-2.0). https://doi.org/10.1007/s13198-021-01138-3

- Monga, R., Aggrawal, D., & Singh, J. (2022). Smart Beta Investing: An Alternative Investment Paradigm in Emerging Indian Equity Market. *Organizations and Markets in Emerging Economies*, *13*(1), 209-237. (Scopus Indexed, ESCI, IF-0.9). doi:10.15388/omee.2022.13.77

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