AN EMPIRICAL ANALYSIS OF THE ADAPTIVE MARKET HYPOTHESIS, MARKET ENVIRONMENT AND INVESTORS SENTIMENT IN NATURAL CALAMITIES

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Submitted

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This is to certify that "***An Empirical Analysis of the Adaptive Market Hypothesis, Market Environment and Investors Sentiment in Natural calamities"*** by Nang Biak Sing (Ph.D. Registration no. MZU/Ph.D./1463 of 16.11.2020) has been written under my supervision.

He has fulfilled all the required norms laid down under Minimum Standards and Procedure for Award of M.Phil./Ph.D. of UGC Regulations 2018. The thesis is the result of his own investigations. Neither the dissertation as a whole nor any part of it was ever submitted to any University for any research degree. He has also published research papers in the UGC care listed and refereed journals which is mandatory prior to submission of Ph.D. thesis under the said UGC Regulations 2018.

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He has fulfilled all the required norms laid down under the Ph.D Regulations 2018. The thesis is the result of his own hard-work and investigation. Neither the thesis as a whole nor any part was ever submitted to any University for any degree or award.

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Declaration

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April, 2024

I, **Nang Biak Sing**, hereby declare that the subject matter of this thesis is the record of work done by me, that the contents of this thesis did not form basis of the award of any previous degree to me or to do the best of my knowledge to anybody else, and that the thesis has not been submitted by me for any research degree in any other University/Institute.

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Chapter 1: Introduction

1.1. Background

Since the mid-20th century, traditional financial theories have dominated the field of finance. The efficient market hypothesis (EMH) has gained remarkable interest and is the focus of investigation. This hypothesis can be traced back to Bachelier (1990), who was the first to mathematically model stock price movements and formulate the principle that the expectation of a speculator is zero. Fama (1965) coined and formalised (Fama, 1970) the EMH theory, which has gained continual attention with extensive examination ever since. Fama (1970), posits a dichotomy between market behaviour and individual decision-making and refers the market as independent or "informationally efficient". This theory asserts that financial markets exhibit rational behaviour manifested through security prices that accurately reflect fundamental intrinsic values. This means that market prices respond to novel information, and no investor can consistently "beat the market" as market prices quickly "reflect" all available information about the intrinsic value of the asset. Numerous studies and hundreds of articles have been published over the past 50 years, but there is no consensus among researchers on whether the market is efficient or inefficient (Baker & Wurgler, 2007; Borges, 2010; Parulekar, 2017; Woo et al., 2020; Worthington & Higgs, 2005).

A new behavioural approach to finance has garnered increasing interest, as evidence has become more convincing (Chandra, 2019, p. 41). The behavioural approach challenged EMH supposition and claimed that people suffer from cognitive and emotional biases and act in a seemingly irrational manner (Barber & Odean, 2001; Shefrin & Statman, 1985; Shleifer & Vishny, 1997; Shiller, 2003). These observations have led some researchers to argue that markets may not always be efficient. Several challenges from various empirical observations and evidences have evolved. Noise trading (Black, 1986) suggests that some market participants trade on irrelevant information or "noise", potentially causing prices to deviate from fundamental values, which is consistent with the research conducted by Zargar and Kumar (2019). Moreover, studies have shown that market anomalies are influenced by the psychology or emotions of investors (Águila, 2009). The detection of anomalies in the markets suggests that certain trading strategies yield higher-average returns (Auer & Rottmann, 2019; Bondt & Thaller, 1987; Greenwald et al., 2004; Komariah & Ramadhan, 2022; McConnell & Xu, 2008; Rozeff & Kinney, 1976; Wang et al., 2013). Shiller (2000, 2015) popularised the idea of "irrational exuberance”, highlighting how investor sentiment and psychological biases can drive market prices away from rational valuations. Considering the prevailing scenario, behaviourists claim that market anomalies arise mainly due to psychological or behavioural reactions to the market, such as overreactions and underreactions in the market (Sharma, 2014), market bubbles (Kapoor, 2017), and market anomalies (Deyshappriya, 2014; Farag, 2013; Narayan & Zheng, 2010). Most empirical literature on behavioural finance like (Bernard & Thomas, 1990; Benartzi & Thaler, 1995; Kahneman & Tversky, 1979; Mehra & Prescot, 2008) are well recognised in contrast with the traditional finance theories. This behavioural approach to finance challenges the assumption of purely rational decision making in traditional finance models. However, the supporters of the EMH challenged behavioural finance by disagreeing that behavioural biases arise only under unique behavioural and market conditions. Corresponding inefficiency arises as humans exhibit idiosyncratic behaviours from time to time only in certain conditions, such as bubbles, crashes, manias, and other real-world trading frictions. (Baberis, 2018; Fama, 1998; Kartašova et al., 2014; Malkiel, 2003; Mishra et al., 2015; Patton & Weller, 2020).

The ambiguity and uncertainty in consensus gave birth to new theories that reconcile the two schools of thought in a natural and satisfying conclusive manner. It is based on the principle that the stock market is neither efficient nor inefficient and follows bounded rationality (Simon, 1955). Campbell et al. (1998) proposed a comparative method for market efficiency, suggesting that financial markets could be evaluated relative to one another rather than in absolute terms. This perspective, while ground-breaking, still utilises traditional efficiency testing methods (Lo & MacKinlay, 1988). Amid the behavioural finance proponents and advocates of the EMH, investor rationality is at the core of the debate. Lo (2004), provides a new theoretical framework, the adaptive market hypothesis (AMH), which reconciles the behavioural aspect of finance with EMH. The AMH proposes that market efficiency is not a fixed state but an evolving condition influenced by environmental factors and the adaptability of market participants. According to Lo (2004), "price reflects as much information as dictated by the combination of environmental conditions and the number and nature of species in the economy". The species here means an individual which seems to have the common behaviour, hedge funds, mutual funds, pension funds, etc., which behave in the same manner even though their investment styles differ. The theoretical foundation of AMH lies in the principles of evolutionary biology and bounded rationality, which offer a sophisticated perspective on the market dynamics. This framework incorporates principles such as competition, mutation, reproduction, and natural selection The AMH is creating a more holistic view of the market which combines the efficient market as a vital model to the current investment orthodox and behavioural finance through evolutionary process (Lo, 2005). This means that the EMH was not false, but rather incomplete, and neither could be disapproved, and traditional finance is as important as behavioural finance to survive in the market.

1.2. Rationale of the study

The motivation of this study is rooted in recognising that financial markets are complex adaptive systems that evolve over time. As such, there is a pressing need to examine whether existing theoretical frameworks adequately capture the subtle and dynamic nature of market behaviour over prolonged timeframes across international economics collaboration. Specifically, it seeks to evaluate whether the AMH provides a more comprehensive and accurate framework for understanding stock return dynamics than the conventional EMH (Lo, 2004). The AMH posits that market efficiency is not a fixed state but rather an evolving characteristic that adapts to changing market conditions and investor behaviours (Lo, 2005, 2012). This perspective offers a potential resolution to the apparent contradictions between market efficiency and the persistent anomalies documented in the finance literature. By examining long-standing stock markets in both developed and emerging economies, this study provides a robust test for AMH across diverse market environments and developmental stages. The inclusion of BRICS (Brazil, Russia, India, China, and South Africa) and G5 (France, Germany, Japan, the United Kingdom, and the United States) countries in this study allows for a comparative analysis of adaptive processes in emerging and developed markets. This approach yields insights into how different market structures and institutional frameworks influence the speed and nature of market adaptation (Neely et al., 2009).

The investigation of stock return dependencies, calendar anomalies, and the efficacy of technical trading rules over prolonged periods aligns with the AMH's core tenets. These elements can serve as indicators of market adaptation processes, potentially revealing cyclical patterns of efficiency and inefficiency, as predicted by AMH. Furthermore, by focusing on markets with rich historical data, this study captures the evolution of market behaviour through various economic cycles, regulatory changes, and technological advancements. This long-term perspective is crucial for testing AMH's assertions of AMH regarding the dynamic nature of market efficiency. This study provides a comprehensive analysis of long-standing stock markets by employing Urquhart's (2013) five-type classification[1] of stock return behaviour. This approach offers an examination of market dynamics over time, aligned with the AMH framework, by recognising the evolving nature of market efficiency. Ultimately, the results contribute empirical evidence to the ongoing debate between efficient and inefficient market paradigms.

Given the importance of investor sentiment in AMH, this thesis also explores a sentiment analysis of investor behaviour during natural calamities, which provides a unique opportunity to investigate investor behaviour under extreme circumstances. Despite the growing body of research on investor sentiment and its influence on financial markets, surprisingly, the impact of natural disasters on stock market returns and the associated public sentiment towards such catastrophic events has received limited detailed examination in the financial literature. While the majority of sentiment research in finance has concentrated on quantifying and analysing broad, generalised indicators of investor sentiment and their implications for asset pricing, the specific ways in which natural disasters influence sentiment towards financial markets and investment decisions remain largely unexplored and unanswered questions. The

[1] Type 1 = Efficient market, Type 2 = Move toward efficient , Type 3 = Switch to inefficient, Type 4 = Adaptive market hypothesis and Type 5 = Market inefficient

effects of natural catastrophes on financial sentiment represents a more nuanced aspect that current sentiment research has not thoroughly explored. Disentangling the precise mechanisms through which catastrophes affect perceptions, risk appetites, and attitudes towards financial markets could lead to novel insights into market operations and pricing in the aftermath of such environmental shocks.

1.3. Significance of the study

This study's multifaceted approach and comprehensive analysis of market behaviour across BRICS and G5 countries make a valuable contribution to the fields of finance, economics, and behavioural studies. These findings have the potential to influence both academic understanding and practical application in global financial markets. This study makes significant contributions to finance and market behaviour research. It addresses a crucial gap by examining AMH in the BRICS and G5 stock markets, offering insights into the market efficiency dynamics in emerging and developed economies. This study introduces an innovative framework for analysing calendar anomalies, enabling more sophisticated cross-market comparisons. Investigating trading strategies based on these anomalies bridges theory and practice and provides valuable insights for investors. Investigating the influence of disaster sentiment on stock returns significantly contributes to behavioural finance theory, providing essential insights for effective risk management strategies and evidence-based policy formulation during crisis periods. The findings demonstrate that market participants' responses to disaster events are not uniformly rational but rather exhibit predictable psychological patterns that translate into quantifiable market movements. Additionally, it provides substantial empirical support for AMH, challenging the traditional static views of market efficiency. This study provides significant implications for market regulators and policymakers, potentially reshaping both theoretical frameworks and practical applications in global financial markets.

1.4. Overviews of markets examination in this study

The selection of G5 and BRICS countries for this study is strategically significant because it offers a comprehensive view of the global market dynamics across developed and emerging economies. This choice provides a unique opportunity to compare and contrast market behaviours in diverse economic contexts. This study delves into the complex dynamics between these two economic groupings that have shaped global economic cooperation and governance: the G5 and the BRICS consortium. This diversity is crucial for examining AMH across various market settings, thereby providing a more robust evaluation of its applicability in different market contexts.

The G5, established in 1974, was an informal group comprising France, Germany, Japan, the United Kingdom, and the United States. It emerged as a response to the economic challenges of the 1970s, focusing on monetary and fiscal policy coordination among major industrialised nations (Bayne & Woolcock, 2011, p.81-92). G5 played a crucial role in addressing issues such as exchange rate volatility and global economic imbalances, although it later evolved into a broader G7. Despite this expansion, G5 continued to meet separately on occasion, particularly when discussing sensitive monetary issues (Bergsten & Henning, 1996). In contrast, the BRICS consortium, a more recent development, represents the growing economic influence of emerging markets in the 21st century. Initially conceptualised by Goldman Sachs in 2001, BRICS includes Brazil, Russia, India, China, and South Africa. This group has become increasingly significant in the global economic landscape, collectively accounting for over 40% of the world's population and approximately a quarter of global GDP (IMF report, 2023).

The markets examined in this study are briefly discussed below:

1.4.1. Standard and Poor 500 (S&P 500)

The Standard & Poor's 500 Index (S&P 500) has emerged as one of the most prominent and widely referenced global stock market indices, serving as a barometer for the United States equity market and, by extension, the broader economy. This index, which tracks the performance of 500 large-cap U.S. companies, has a rich history that reflects the evolution of financial markets and investment practices, traced back to 1923 when the Standard Statistics Company introduced its inaugural stock market index, encompassing 233 companies (Shiller, 2001). A significant milestone occurred in 1941, with the merger of Standard Statistics and Poor's Publishing, forming Standard & Poor's (S&P), which set the stage for developing more comprehensive market indices. The year 1957 marked the official inception of the modern S&P 500 as we know it today, expanding the index to include 500 companies and establishing a more robust representation of the U.S. stock market (Bekaert et al., 2014). This expansion coincided with the growing sophistication of financial markets and increasing demand for more accurate market benchmarks.

The S&P 500 Index determines its value through the market capitalisation of companies adjusted for their free-float shares. To ensure transparency in reporting, the S&P 500 provides detailed explanations of the free-floating market capitalisation methodology. This openness allows investors and analysts to understand how the index value is derived and what factors influence its movements. The index is calculated as:

$$\text{Index Level} = \frac{\sum_{i=1}^{n} P_i \times Q_i}{Divisior} \tag{1.1}$$

Where P_i is the price of the stock, Q_i is free float rate based on the number of shares available for public trading and the divisor is adjusted for corporate actions like stock splits, dividends, or changes in the index composition to normalise the total value of the index.

The S&P 500 serves as a crucial barometer for both U.S. financial markets and the global economic landscape (Berk & DeMarzo, 2020). This index encompasses 500 major American corporations spanning diverse industries, and offers a comprehensive view of market performance (Bodie et al., 2018). While shifts in individual large-cap stocks can sway the index, substantial movements typically stem from broader sectoral trends or significant macroeconomic events such as monetary policy adjustments or international geopolitical tensions (Malkiel, 2019). The historical price movement of S&P 500 over the period from 1990 to 2022 is depicted in Figure 1.1.

Figure 1.1: S&P 500 index closing price

Source: Trading Economics database

1.4.2. FTSE 100

The FTSE 100, also known as the Financial Times Stock Exchange 100 Index or informally as the "Footsie", is a share index of the 100 companies listed on London Stock. The FTSE 100, established in 1984, is a prominent share index representing the 100 largest companies by market capitalisation on the London Stock Exchange. The index uses a free-float market-capitalisation-weighted methodology that considers only publicly available shares for trading. The FTSE 100 index computation begins by establishing an initial arbitrary value of 1,000 on its inception date. It is calculated in real time and published every 15 seconds during trading hours. FTSE 100 undergoes quarterly reviews in March, June, September, and December, during which companies may be added or removed based on their market cap ranking. The FTSE 100 index employs a methodology inspired by the Paasche formula to maintain accuracy and continuity during corporate actions. This approach involves a two-step process that spans days immediately before and after a significant event affecting one or more of its constituent companies. The index is computed as:

$$FTSE\ 100\ Index = \frac{\frac{Total\ Market\ value}{(Share\ price \times Number\ of\ shares \times Free\ float\ adjust\ Factor)}}{Index\ Divisor} \tag{1.2}$$

The historical price movement of S&P 500 is depicted in Figure 1.2. The composition of the FTSE 100 price movement has evolved, reflecting changes in the UK's corporate landscape and global economic shifts. The index has served as a key indicator of the UK's economic performance over the past four decades (Michie, 2001). The index experienced significant growth during the dot-com boom, reaching 6950.6 points in December 1999, before declining sharply in the subsequent bust (Shiller, 2015). The global financial crisis of 2007-2009 severely impacted FTSE 100, causing it to lose nearly half its value (Blundell-Wignall & Atkinson, 2009). Post-crisis recovery led to new record highs, with an index surpassing 7000 points in April 2015 (FTSE Russell, 2023). Recent years have seen further volatility, influenced by events such as Brexit and the COVID-19 pandemic (Baker et al., 2020). The index serves as a benchmark for fund performance and forms the basis for numerous index-tracking funds and derivatives influenced by global economic factors, not just UK-specific events.

Figure 1.2: FTSE 100 index closing price

Source: Trading Economics database

1.4.3. CAC 40

The CAC 40 (Cotation Assistée en Continu 40) is the benchmark of the French stock market index. CAC 40 was introduced on 15 June 1988 with a base value of 1,000 points was set on 31 December 1987. It was created to represent the performance of the 40 most significant values among the 100 largest market capitalisations in the Paris Bourse (now Euronext Paris). Initially, the index was calculated by using a price-weighted measure. In 2003, it switched to free-float-adjusted market capitalisation weighting.

$$CAC\ 40\ index = \frac{\sum_{i=1}^{N} P_i \times Q_i \times F_i \times C_i}{D} \times Base\ Point \tag{1.3}$$

Where, P_i is price of each stock, Q_i is number of shares of the company, F_i is free-float factor, C_i is a capping factor, the weight of each component is capped at 15% of the index's total free-float market capitalization. D is the index divisor. The performance of CAC 40 during critical periods, such as the dot-com bubble and 2008 Global Financial Crisis, offers valuable insights into the strengths and limitations of traditional index construction methods. The index's all-time high of 6,922.33 points on 4 September 2000 followed by a subsequent crash, underscores the potential for market irrationality and challenges the assumptions of traditional finance. The historical price movement of CAC 40 index is depicted in Figure 1.3.

Figure 1.3: CAC 40 Index closing price

Source: Trading Economics database

1.4.4. DAX 30

The DAX 30 (Deutscher Aktienindex 30) is Germany's premier stock market index, representing the performance of the 30 largest and most liquid companies trading on the Frankfurt Stock Exchange. The DAX was established on 1 July 1988 with a base value of 1,000 points. Its creation coincided with a period of increasing globalisation and the modernisation of financial markets (Karolyi & Stulz, 2003). The index was designed to provide a reliable barometer for the German equity market, which was gaining prominence in the global financial landscape following the country’s post-World War II economic resurgence.

Initially, the DAX employed a capitalisation-weighted methodology, which is a common approach in traditional finance theory (Markowitz, 1952). However, recognising the limitations of this method, particularly its susceptibility to overweighting overvalued stocks, the index transitioned to free-float adjusted market capitalisation weighting in 2002 (Deutsche Börse Group, 2023). This shift aligned with evolving academic perspectives on index construction as articulated by Arnott et al. (2005) in their work on fundamental indexation. DAX 40 was computed using the following formula:

$$DAX\ 40\ index = K_T \times \frac{\sum_{i=1}^{N} P_i \times Q_i \times F_i \times C_i}{\sum_{i=1}^{N} P_0 \times Q_0} \times Base\ Point \quad (1.4)$$

Where, P_i is the price of enterprise stock, Q_i is the number of shares of the company, F_i is the free-float factor, C_i is the capping factor (current adjustment factor). P_0 is the final stock price of company at trading day before first introduction of index Deutsche Börse. Q_0 is the number of share of company at trading day before first introduction of index Deutsche Börse and K_T is index specific concentration factor.

DAX 30 historical performance provides a nuanced picture of Germany's economic trajectory and its position within the global financial landscape. The DAX has experienced several significant phases: Post-Reunification Period (1990-1992), Dot-com Era (1997-2003), Global Financial Crisis (2008-2009), European Debt Crisis

(2010-2012), and the COVID-19 pandemic and global economic uncertainties. The index's reactions to various economic cycles offer valuable data for studying market efficiency, investor behaviour, and the impact of macroeconomic factors on equity markets. The historical price movement of DAX 30 index is depicted in Figure 1.4.

Figure 1.4: DAX 30 index closing price

Source: Trading Economics database

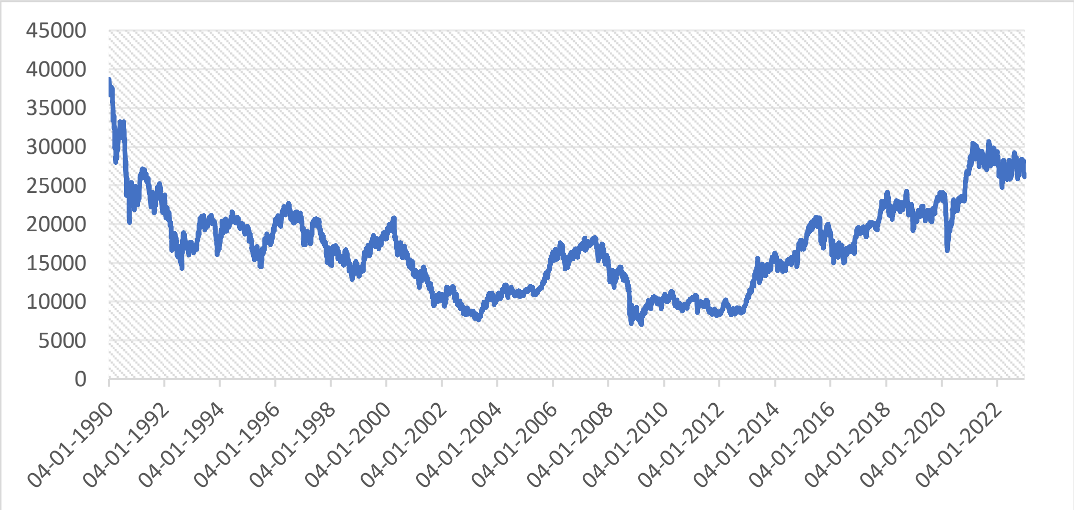
1.4.5. NIKKEI 225

The Nikkei 225, also known as the Nikkei Stock Average, is Japan's premier stock market index and one of the most widely watched global equity benchmarks. The Nikkei 225 was first published on 7 September 1950 by the Nihon Keizai Shimbun (Nikkei) newspaper, with a base value of 176.21 yen (Hamao et al., 1991). Its creation coincided with Japan's post-war economic reconstruction period, serving as a barometer for rapid industrialisation and economic growth (Ito & Weinstein, 1996). The Index is calculated as follows:

$$Nikkei\ 225\ index = \frac{\sum p}{d}$$

where p is the price of the component stocks, and d is the divisor. Unlike many modern capitalisation-weighted indices, the Nikkei 225 employs a price-weighted methodology, similar to the Dow Jones Industrial Average in the United States. This approach, rooted in traditional finance theory, calculates the index value as the arithmetic average of the stock prices of its constituent companies (Hamao et al., 1991). The 225 components were selected from the First Section of the Tokyo Stock Exchange based on liquidity and sector balance. The selection is reviewed annually with changes implemented to maintain the index's representativeness of the broader market. The index is calculated every five seconds during trading hours, reflecting the dynamic nature of modern financial markets. The historical price movement of the Nikkei 225 is shown in Figure 1.5.

Figure 1.5: Nikkei 225 Index closing price



Source: Trading Economics database

1.4.6. SENSEX 30

The BSE SENSEX 30, also known as the S&P BSE SENSEX or simply SENSEX, contains a basket of 30 constituent stocks of the largest and most actively traded stocks. It was conceived as a means to measure the overall performance of the BSE, representing the benchmark stock market index of the Bombay Stock Exchange (BSE) in India. SENSEX was first compiled in 1986, with the base year set as 1978-79 and a base value of 100 points. Initially, SENSEX employed a full-market capitalisation-weighted methodology. However, recognising the need for a more representative index, it transitioned to free-float market capitalisation weighting in September 2003. This shift aligned with global best practices and addressed concerns about the index's susceptibility to manipulation through changes in non-traded shares (Dutta, 2005). The composition of SENSEX is reviewed semi-annually, and changes are made based on factors such as market capitalisation, liquidity, and sector representation. The Index is calculated as follows:

$$Sensex\ 30\ Index = \frac{Total\ free\ Float\ Market\ capitilsation}{Base\ market\ capitlisation} \times Base\ index\ value \quad (1.6)$$

The BSE SENSEX, a key indicator of India's economic health, shows a significant correspondence with economic events, policy change, or global trends over inception. During the economic liberalisation of 1991, SENSEX rose from about 1,000 to over 4,000 points, reflecting the positive impact of reforms (Basu & Wadhwa, 2013, p. 290-318). The technology boom of 1998-2000 saw an index surge from around 3,000 to over 6,000 points driven by IT stocks (Joshi, 2018). The global financial crisis of 2008-2009 had a significant impact, from its peak of 21,206 in January 2008 to a low of 8,160 in March 2009, mirroring the worldwide economic downturn (Kumar & Vashisht, 2009). Narendra Modi, as Prime Minister in 2014, triggered a bullish trend, with SENSEX crossing 25,000 marks for the first time (Mishra, 2021). The COVID-19 pandemic has caused extreme volatility in the index. It dropped to approximately 25,981 in March 2020 before rebounding to cross 50,000 in January 2021, showcasing the market's resilience and the impact of economic stimulus measures (Rakshit & Neogi, 2021). Later, the SENSEX continued its upward trajectory, crossing the 60,000-point milestone on 24 September, 2021 (Thakur, 2021). The historical price movement of BSE Sensex 30 index is depicted in Figure 1.6.

Figure 1.6: BSE Sensex 30 index closing price

Source: Trading Economics database

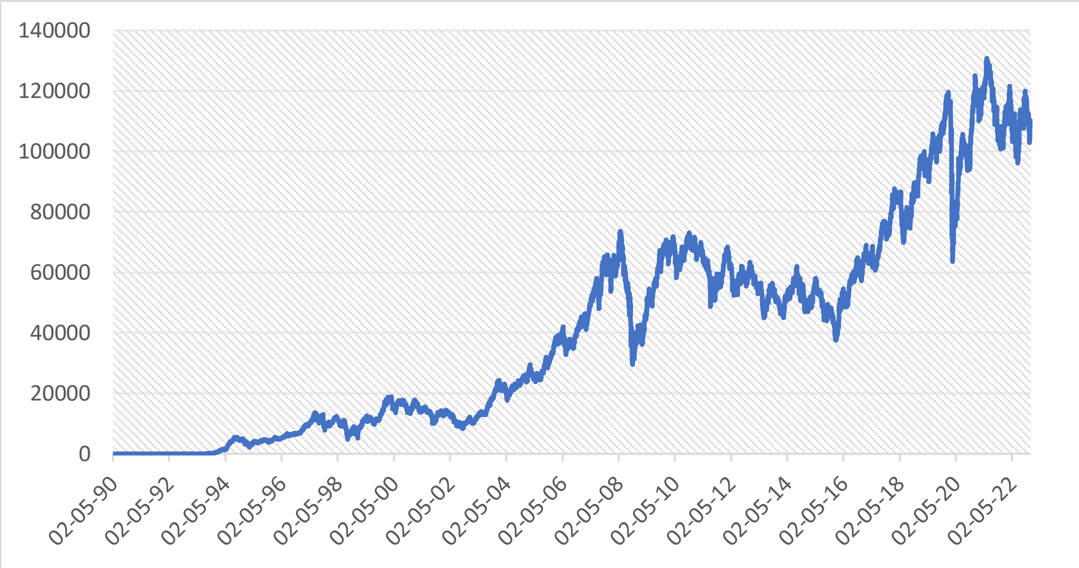
1.4.7. IBOVESPA

The IBOVESPA, (or Índice Bovespa), is the benchmark stock market index of most actively traded and representative stock on the B3 (Brasil Bolsa Balcão), also Brazil’s primary stock exchange and the oldest index in Brazil. The IBOVESPA was established on 2 January 1968 with a base value of 100 points, coinciding with a period of rapid industrialisation in Brazil, known as the "Brazilian Miracle" (Baer, 2014). The index is constructed using a weightage market value attribution to the free-float rate, subject to liquidity-based weight capitalisation. The formulation of the IBOVESPA Index is determined using Equation (1.4).

The performance of the index is crucial in establishing Brazil as a major emerging market. The IBOVESPA experienced significant notable price movement in response to global trends in the stock market; the Asian Financial Crisis caused a significant drop in the index by approximately 30% in October 1997 due to contagion effects (Tabak & Lima, 2013), and the 2008 Global Financial Crisis caused the IBOVESPA to fall by about 60% between May and October 2008 (Vartanian, 2018). The index saw significant growth, rising from around 10,000 points in 2002 to over 70,000 points by 2008, driven by strong commodity prices (Chaves & Vieira, 2013). The index experienced high volatility owing to political instability and corruption scandals, dropping to approximately 38,000 points in January 2016 (Gaio et al., 2018).

Moreover, the index plummeted by about 45% in response to the global pandemic (B3, 2021). The historical price movement of IBOVESPA is represented in Figure 1.7.

Figure 1.7: IBOVESPA index closing price



Source: Trading Economics database

1.4.8. JALSH

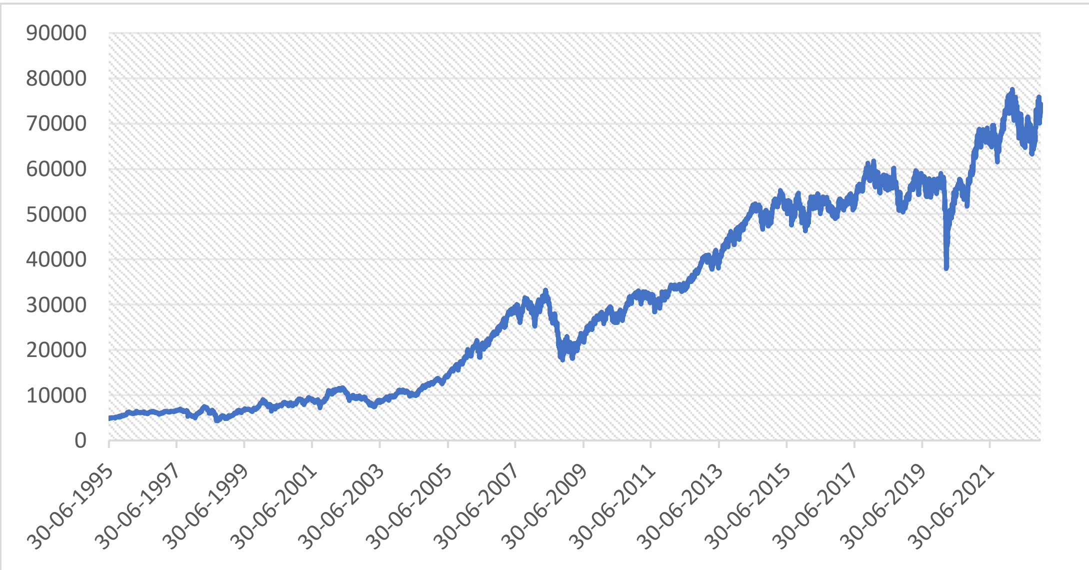
The Johannesburg Stock Exchange (JSE) stock index (JSE All-Share Index, or JALSH) is a comprehensive price index representing 99% of the JSE's market cap and trading volume. The index was first published on 2 October 1978 and later took over the calculation of index by FTSE Russell on 24 June 2002 with a base value of 10,815.08 points. The FTSE/JSE Africa Index Series is an arithmetic index weighted by free-float market capitalisation, where each company's impact on the index is proportional to its investable market value, calculated as the product of its shares-in-issue, share price, and free-float factor. The index is computed as:

$$JSE\ All\ Share\ Index\ at\ time\ t = \frac{\sum_{i=1}^{N} N_i \times P_i \times F_i \times SW_i}{B_i} \tag{1.8}$$

where, N_i is the number of share issues for company at time t, P_i is the price of stock in local currency, F_i is the free-float factor, SW_i is the style weightage of a company. B_i is the index base adjusted from past capital alteration. The index was updated every 60 s and reviewed semi-annually.

The JALSH underwent significant transformations in response to global technological advancements in the mid-1990s. Its evolution offers a unique perspective on the development of financial markets in emerging economies and the challenges of operating in a complex socioeconomic environment. JALSH was founded to facilitate the burgeoning mining industry's capital needs (Jefferis & Smith, 2005). Initially, it primarily listed mining and financial services companies, reflecting South Africa's resource-based economy. The exchange's early years were characterised by relatively low liquidity and limited foreign participation, largely due to the country's political isolation during the apartheid era (Andreasson, 2011). The historical price movement of JSE All share is depicted in Figure 1.8.

Figure 1.8: JSE All Share (JALSH) Index closing price



Source: Trading Economics database

1.4.9. MOEX

In 1992, the Moscow Interbank Currency Exchange (MICEX) was established, focusing primarily on foreign exchange (FX) trading. The Russian Trading System (RTS) emerged as another major exchange specialising in stocks and derivatives. Later, MICEX and RTS merged, forming the Moscow Exchange (MOEX) in 2011, with a base value of 100 points on 22 September 1997. Over the years, the index has undergone several methodological changes to better represent the Russian market and to align with international standards. These changes included adjustments to the free-float calculation, the introduction of liquidity criteria, and the implementation of capping mechanisms to prevent single-stock dominance (Fedorova & Pankratov, 2010). The index computation is parallel to that in Equation (1.3). The index is calculated in real time during the Moscow Exchange trading hours, and its composition is typically reviewed quarterly. MOEX Index experience some significant economic events like during Global Financial Crisis of 2008-2009, the index experienced a dramatic decline of over 70 percent, Russian Financial Crisis of 2014-2015 brought another period of significant volatility to the index, COVID-19 pandemic and Russian invasion of Ukraine in 2022 triggered an unprecedented 33% single-day plunge in the index on February 24. Moreover, on 24 February 2022 the Moscow Exchange halted all trading activities indefinitely and pended further announcements. Historical price movement of the index is shown in Figure 1.9.

Figure 1.9: MOEX index closing price

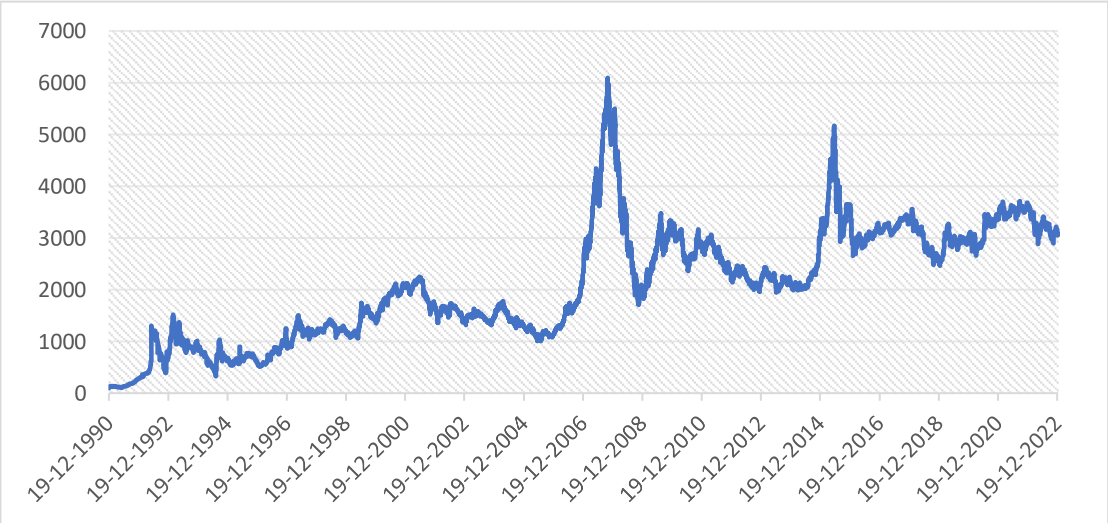
Source: Trading Economics database

1.4.10. SSEC

The Shanghai Stock Exchange Composite Index (SSEC) can be traced to the late 19th century. The first share list appeared in June 1866, and by the 1930s, Shanghai emerged as the financial centre of the Far East, hosting the largest stock exchange in Asia (Wu & Xu, 2018). The modern incarnation was established on 26 November 1990 and commenced operations on 19 December of the same year. The base value was set to 100 points on 19 December 1990. The SSE Composite Index serves as the exchange's primary benchmark and provides a broad measure of market performance. This capitalisation-weighted index encompasses all A- shares and B-shares listed on the exchange.

The Shanghai Stock Exchange is one of the world's largest stock exchanges by market capitalisation, playing a crucial role in China's financial landscape and in increasing global financial markets (Carpenter & Whitelaw, 2017). The computation of the index value formulation is in line with the Paasche-weighted composite price index in Equation (1.2). The Shanghai Stock Exchange is one of the world's largest stock exchanges due to market capitalisation, playing a crucial role in China's financial landscape and increasing global financial markets (Chen et al., 2019). The SSE Composite Index has faced numerous challenges since its inception in 1990. During the Asian Financial Crisis of 1997-1998 (Fernald & Babson, 1999), the dot-com era experienced modest growth (Laurenceson & Chai, 2003). The 2008 financial crisis caused a dramatic 73% decline (Zhang & Peng, 2014). The US-China trade war (Liu & Woo, 2018) increased volatility, overall decline, and resilience during the 2020 COVID-19 pandemic. Figure 1.10 provides a comprehensive visual representation of these market movements.

Figure 1.10 SSE Composite Index closing price



Source: Trading Economics database

1.5 Research Design

1.5.1. Statement of the problem

Over the past several decades, the longstanding debate between the proponents of the EMH and Behavioural Finance (BF) has been a central issue in financial economics. As financial research progressed, a significant divide emerged among scholars regarding market behaviour and efficiency. This schism resulted in two distinct schools of thought: adherents of the EMH and advocates of the BF. EMH proponents argue that markets operate efficiently, with asset prices quickly incorporating new information. They contend that systematically predicting security returns is unfeasible, and speculative activities yield no excess profits. In stark contrast, BF supporters maintain that markets exhibit inefficiencies. They reason that, if markets are truly efficient, there would be no incentive for stock analysis or trading, as such activities would not generate profits. This fundamental disagreement has led to a lack of consensus regarding the nature of stock market behaviours. The absence of a unified understanding poses significant challenges for both asset allocation strategies and effective portfolio management practices. The conflicting perspectives on market efficiency and investor behaviour have sparked an attempt to reconcile the EMH from an evolutionary perspective. The AMH reinvestigation of the market as a holistic view is incorporated into the standard lexicon of financial investment theory.

Studying an evolutionary perspective toward standard finance theory can be quite complex, as it may not be possible to retrieve the required data from individuals or groups. Lo (2004) states that arbitrage opportunities arise episodically over time under certain market environments, but the author does not provide a clear definition of "certain market environments." It is intricate to analyse the various types of market environments in which investors interact (e.g., natural resources, current environmental conditions, market microstructure, legal and regulatory restrictions, and tax effects). The AMH proposes a cyclical model of market efficiency, suggesting that markets oscillate between periods of efficiency and inefficiency (Lo, 2004; Urquhart & McGroarty, 2016). Since its inception, the AMH has prompted a re-evaluation of market efficiency concepts. Recent empirical studies have focused on examining the varying degrees of efficiency in both developed and emerging markets through the lens of AMH (Ghazani & Araghi, 2014; Noda, 2016). Notably, many markets in developed economies, previously considered efficient in absolute terms under the EMH framework, have been found to exhibit cyclical patterns of efficiency and inefficiency when analysed using the AMH approach (Ito & Sugiyama, 2013; Urquhart & McGroarty, 2016). The unique characteristics of emerging markets often render findings from developed economies inapplicable (Bekaert & Harvey, 2002). Given the unique characteristics of developing markets, investigating the inefficient markets in developing economies through the framework of the Adaptive Market Hypothesis (AMH) is crucial. Moreover, a comparative analysis between emerging and developed economies provides an opportunity to assess the validity of AMH across diverse market structures and developmental stages.

Similarly, Calendar anomalies contributed in market inefficiencies. Earlier researchers suggested that market anomalies often have a limited lifespan (Dimson & Marsh,2001; Scwert, 2003). They argue that as investors become more aware of these irregularities, market liquidity improves, and participants adapt to the changing environment. Despite extensive research on the persistence of calendar anomalies, findings remain inconclusive. The AMH proposes that market efficiency fluctuates over time, suggesting a cyclical pattern of efficiency and inefficiency. This framework opens new avenues for investigating calendar anomalies in stock returns. Specifically, it encourages researchers to examine how calendar-based patterns evolve over time and how they differ under varying market conditions. This dynamic approach to studying calendar effects aligns with the AMH's view of changing market efficiency.

Furthermore, the AMH framework suggests that market efficiency and price mechanisms evolve in response to external shocks (Lo, 2012). Existing body of literatures adequately explores how natural disasters impact the stock behaviour of countries or regions. Yet, current body of knowledge fails to provide a comprehensive analysis on how natural disasters change sentiment and decision-making processes among market participants. This knowledge gap impedes our understanding of market resilience and efficiency in the face of catastrophic events. Moreover, the lack of a detailed examination of disaster-induced mood sentiment on stock returns leaves unexplored questions about potential anomalies or inefficiencies that may arise in post-disaster periods.

1.5.2 Research gap

Numerous studies have investigated market efficiency using various approaches using parametric or nonparametric tests. Despite the widespread application of these tests, a thorough comparative analysis of their relative testing approaches for capturing the time-dependent dynamics of stock returns in the BRICS and G5 markets remains unexplored. The contradictory evidence regarding the presence of nonlinear dependencies in stock returns necessitates further investigation to reconcile these findings in developed and emerging financial markets. Furthermore, the persistent observation of calendar-based anomalies in stock returns provides inconclusive empirical evidence and warrants further investigation. The existing literature has documented mixed findings regarding the presence and persistence of calendar effects, such as day-of-the-week and month-of-the-year anomalies, across different markets and time periods. This suggests that these anomalies may exhibit time-varying or market-specific characteristics that are limited to a few markets and remain underexplored using a symmetric and asymmetric Generalised Autoregressive conditional heteroscedasticity (GARCH) model. Finally, the existing literature explores the impact of natural disasters on stock behaviour in various regions; however, it lacks a comprehensive analysis of how these events change sentiment and decision-making among market participants. Additionally, there is a lack of detailed examination of disaster-induced mood sentiment on stock returns, leaving unexplored questions about the potential anomalies or inefficiencies that may arise in post-disaster periods. To the best of the author knowledge, no studies have examined the intricate relationship between the sentiment-based natural disaster index and stock returns, particularly in India.

1.5.3. Research questions

In light of the concerns discussed earlier, it is crucial to answer the following research questions.

1. Are stock price changes dependent or time dependent, do market exhibit time varying dependent or adaptive in stock price movements?
2. To what extent are market anomalies present in developed and developing markets and how does these anomalies evolve overtime?
3. Under which specific market conditions do calendar anomalies produce significant returns, and how do these conditions vary between developed and developing countries?
4. How do trading strategies perform across different markets, and which strategies demonstrate superior risk-adjusted returns in an explicit market?
5. How does investor sentiment in the stock market respond to natural calamities, and does this response differ across sectors?

1.5.4. Objectives of the study

Given the rationale of the study and the problem statement, the primary objective of this research is to examine market efficiency and calendar anomalies within the Adaptive Market Hypothesis (AMH) framework in the BRICS and G5 markets, as well as investor sentiment during natural calamities. The specific objectives of this study were as follows:

1. To examine the time dependence of stock return and adaptive market behaviour of return in developed (G-5) and developing (BRICS)
2. To examine the existence of calendar market anomalies in developed and developing markets
3. To investigate the presence of adaptive market pattern in calendar anomalies
4. To determine whether trading strategies outperform in various market environments
5. To examine the sentiment behaviour of the stock dynamics during natural calamities

1.5.5. Hypotheses of the study

H_1: The behaviour of the stock price exhibits time-varying return predictability consistent with the adaptive market hypothesis.

H_{1a}: The BRICS markets exhibit significant linear time-varying patterns.

H_{1b}: The BRICS markets exhibit significant nonlinear time-varying patterns.

H_{1c}: The G-5 markets exhibit significant linear time-varying patterns

H_{1d}: The BRICS markets exhibit significant nonlinear time-varying patterns.

H_{1e}: The degree of market efficiency changes over time differs in the G-5 and BRICS markets.

H_2: The stock market exhibits significant calendar anomalies

H_{2a}: There is a significant day of the week effect on BRICS and G5 market returns.

H_{2b}: There is a significant month-of-the-year effect on the BRICS and G5 market returns.

H_{2c}: There is a significant turn-of-the-month effect on the BRICS and G5 market returns.

H_3: There is a significant adaptive nature of calendar effects

H_{3a}: There are significant time-varying calendar effects in BRICS financial markets.

H_{3b}: There are significant time-varying calendar effects in G-5 financial markets.

H_{3c}: The adaptive patterns of calendar effects differ between G-5 and BRICS markets.

H_4: There is significant profitability in trading strategies based on identified calendar anomalies

H_{4a}: An implied trading strategy (ITS) based on identified calendar anomalies generates higher returns than a simple buy-and-hold (BH) strategy.

H_{4b}: The profitability of ITS differs between the developed and developing markets.

H_5: Investor sentiment during natural calamities has a significant impact on stock market returns

H_{5a}: Natural calamities have a significantly negative impact on stock market returns.

H_{5b}: Hydrological disasters have substantial adverse effects on stock returns.

H_{5c}: Climate-related disasters and extreme weather events have a significant negative impact on the stock returns.

H_{5d}: Natural disaster sentiment has a significantly negative impact on sectoral returns.

H_{5e}: The impact of natural disaster sentiment on stock returns varies for different types of disasters.

1.5.6. Methodological scope

This study adopts a quantitative research approach, utilising secondary data on stock returns from the BRICS and G5 markets. The data are obtained from the Trading Economics database and the official websites of the respective countries' stock exchanges, covering a period of 32 years (1 January 1990 to 31 December 2022) based on the availability of data. This study employed a comprehensive quantitative research approach to achieve its objectives. To investigate the time dependence and cyclical nature of market behaviour, the analysis utilises linear dependency tests such as autocorrelation, variance ratio, and unit root tests, as well as a battery of nonlinear tests such as the McLeod Li test, Engle LM test, and BDS test. To examine the existence and adaptive nature of calendar anomalies, this study utilises models from the

(GARCH) family: symmetric (GARCH) and asymmetric (EGARCH) within a rolling fixed-window framework of three years. To evaluate the performance of different trading strategies under varying market conditions, the study compares a buy-and-hold (BH) strategy with an implied calendar anomalies trading strategy (ITS). The Autoregressive Distributed Lag (ARDL) approach was employed to investigate the long-run cointegration, short-run dynamics, and stability of the relationship between disaster sentiment and sectoral stock returns. Finally, the Granger causality test is applied to examine the potential causal relationships between proxies for investor sentiment and sectoral stock returns.

1.6. Structure of the Thesis

Chapter 1 commences with the background of the study, delineating its motivation, significance, and an overview of the market analysis. Subsequently, the research design was delineated, encompassing the identification of the problem and research gap, followed by the research questions, objectives, hypotheses, and methodological scope. The final section presents the structural organisation of the thesis.

Chapter 2 provides a literature framework covering the key areas that lay the foundation for this thesis. It begins with the Efficient Market Hypothesis (EMH) and discusses its development, forms, assumptions, and problems. The chapter then explores various stock market anomalies, including the value premium, momentum, reversal effect, disposition effect, bubbles, herd effect, size effect, and calendar anomalies. Trading rules and technical analysis are examined, covering the history of technical analysis, the buy-and-hold strategy, and filter rules. This chapter also explores investor sentiment, its impact on stock returns and volatility, factors influencing market fluctuations, and sentiment during extreme circumstances. The Adaptive Market Hypothesis (AMH) is introduced, along with its key principles, implications, and recent studies in developed and emerging markets. This section highlights the dynamic nature of market efficiency and how it evolves over time. The chapter concludes by identifying a research gap in the evaluation of time-dependent returns within the AMH framework, particularly in comparing emerging and developing countries. This gap sets the stage for the current study's focus on investigating the dynamic market assumptions of AMH across diverse market settings.

Chapter 3 studies a comparative analysis of time-dependent stock returns in BRICS and G-5 countries, employing both linear and nonlinear tests to explore the applicability of the Adaptive Market Hypothesis (AMH) in explaining return behaviour. The study implements linear tests, such as autocorrelation, variance ratio, and unit root tests for stationarity. Subsequently, the returns undergo a whitening process using AR and AR-GARCH methods to eliminate linear correlation. The resulting residuals are then subjected to nonlinear tests including the McLeod Li test, Engle LM test, and BDS test. To assess the evolution of market behaviour over time, the analysis is conducted using three-year subsamples, which provide a balance between sufficient observations for accurate evaluation and an adequate number of results to discern temporal patterns. The observed return behaviours are then classified into five predefined categories, offering insights into the dynamic nature of market efficiency across different economic contexts.

Chapter 4 explores the temporal dynamics of calendar anomalies and the adaptive calendar effect by analysing well-established seasonal patterns in financial markets. This study examines the presence and evolution of calendar anomalies in stock returns and volatility using GARCH models, investigates their adaptive nature through fixed-window analysis, and assesses the potential profitability of exploiting these anomalies by comparing the buy-and-hold and implied trading strategies. The research focuses on three primary calendar anomalies: the Monday effect, the January effect, and the turn-of-the-month effect. The observed patterns in each market are classified into five predefined categories and the profitability of these calendar effects is assessed using a buy-and-hold trading strategy and implied trading strategies.

Chapter 5 examines the impact of natural disasters on the Indian equity market. This chapter initially examines the impact of geophysical, hydrological, and meteorological natural disasters on investor sentiment and stock market returns, explores how these events influence different sectors and develops a disaster sentiment-based index to capture investor perceptions of climate-related risks. The classification of natural calamities, construction of a disaster sentiment index using Google search data, and inclusion of control variables such as the Market Mood Index and VIX, along with descriptive statistics and correlation analysis of the sentiment indices form parts of the chapter. The methodology employs OLS regression, Kruskal-Wallis tests, ARDL modelling for cointegration and long-run/short-run dynamics, and Granger causality tests to analyse the impact of natural disasters and investor sentiment on Indian stock market returns across various sectors.

Finally, Chapter 6 summarises the research findings, draws conclusions and implications, discusses the limitations of the study, and suggests avenues for future research.

Chapter 2: Theoretical and Literature Framework

2.1. Introduction

In this chapter, the literature framework covers several key areas related to market efficiency and anomalies: the Efficient Market Hypothesis (EMH), including its earlier and recent development, forms, assumptions, and problems; followed by various stock market anomalies, such as the value premium, momentum, reversal effect, disposition effect, bubble effect, herd effect, size effect, and calendar anomalies. The review also explores trading rules and technical analysis, including the history and development of technical analysis, buy-and-hold strategy, and filter rules (implied trading strategy). Investor sentiment is another important topic, covering its impact on stock returns and volatility, factors influencing stock market fluctuations, and investor sentiment in extreme circumstances. The Adaptive Market Hypothesis (AMH) along with its key principles, implications, and recent studies in developed and emerging markets are presented in this section.

2.2. The Efficient Market hypothesis

The origins of the Efficient Market Hypothesis (EMH) can be traced back to the pioneering work of Louis Bachelier, a French mathematician who introduced the notion of stock prices following a random pattern in his 1900 doctoral thesis, "The Theory of Speculation" (Bachelier, 1900). In 1953, Kendall, a British statistician, presented a groundbreaking paper that examined the behaviour of stock and commodity prices in search of regular cycles (Kendall, 1953). His findings revealed that instead of exhibiting predictable patterns, the price series appeared to be drawn from a sequence of random numbers, implying that successive price changes were independent of one another. This observation challenges the prevailing notion of cyclical patterns in financial markets. Supporting Kendall's findings (Osborne, 1959; Roberts 1959) published further evidence for the random behaviour of stock return. They demonstrated that the cumulative sum of random numbers closely resembled the time series of stock prices, akin to the outcomes of a roulette wheel, where each spin is statistically independent. Osborne (1959) drew an analogy between stock price behaviour and Brownian motion, a phenomenon observed in the random movement of small particles suspended in a liquid medium. These early insights paved the way for the formal development of the Efficient Market Hypothesis by Eugene Fama in the 1960s, and its subsequent refinement over the following decades (Fama, 1970, 1991). The EMH posits that in an efficient market, asset prices fully reflect all relevant information, making it impossible for investors to consistently earn abnormal returns through superior analysis or market timing.

2.2.1. Recent Development of EMH

The EMH is a seminal theory in finance that has significantly influenced the development of other theories, such as the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964) and the Arbitrage Pricing Theory (APT) (Ross, 1976), proposed by Fama (1970, 1990), based on Samuelson's Random Walk Model (RWM) (Samuelson, 1965). His work laid the groundwork for the principle that stock prices are inherently unpredictable and follow random walks. The EMH suggests that in an efficient market, security prices adjust rapidly to the influx of new information, rendering future price movements unpredictable (Bhat, 2008, p.336-377). Consequently, investors without prior research have the same expected returns as those relying on technical analysis or analysts' recommendations (Menkhoff, 2010). The Hypothesis (EMH) posits that markets are fair, and no investor can consistently outperform the market, even with in-depth analysis using three forms of information (Fama, 1970). Consequently, it is impossible to generate extraordinary profits through expert stock selection and market timing. The only way an investor can potentially outperform others is by investing in riskier assets. Samuelson (1965) and Fama (1970) suggested that EMH implies that share prices should adjust rapidly to new information, with current stock prices fully reflecting all available information and following a random-walk pattern.

The modest and sensible statement of the market efficiency hypothesis is that “security prices at any time fully reflect all available information”. The EMH is a theory which states that the given financial market prices mirror all the available information at a given time, the “type” and “source” of information is already reflected in stock prices (Thomset, 2018). Reilly and Brown (2006, p.170-195) stated that “the prices of securities change rapidly to the infusion of new information”. (Kuepper,

2019) said that it is “investment theory, where share price reflects all the available information and constant alpha generation is possible, neither fundamental nor technical analysis can produce consistent alpha”. This means that the movement of the stock price follows a rational behaviour of random movement, and the historical price has no relationship with the forthcoming movements of the price, and vice versa. This theory has significant implications for investment strategies, market efficiency, and the role of fundamental and technical analyses in generating consistent abnormal returns. As investment activities in financial markets continue to accelerate, understanding the efficiency of emerging markets is crucial for investors. Efforts to identify underpriced or overpriced securities would be a futile exercise if the equity market in which an investor operates is efficient. The EMH posits that rational investors who can predict prices accurately are unable to consistently beat the market if they are truly efficient. According to this theory, the only way for investors can obtain higher returns by investing in riskier assets (Fama 1970; Malkiel 2003). Consequently, actively managed portfolios with the aim of outperforming the market may be unsuccessful, as stock prices are assumed to reflect all available information, and passive investment strategies such as indexing may be more appropriate in efficient markets (Bogle, 2009; Malkiel, 1995).

2.2.2. Forms of the efficient market hypothesis

Fama (1990) typically categorized the efficient market hypothesis into three forms, each representing a different level of market efficiency based on the type of information that is assumed to be reflected in asset prices.

1. **Weak form**: Proponents of the weak-form EMH argue that technical analysis, which involves using historical price and volume data to forecast future price movements, is ineffective in beating the market. This form asserts that asset prices follow a random-walk pattern, implying that past sequences of prices, rates of return, trading volumes, block trades, and other historical trading data contain no valuable information for forecasting future price movements. The weak form of efficiency implies that examining historical rates of return and

prior research findings cannot provide an advantage in predicting the expected future returns in an efficient market.

2. **Semi-strong form:** The semi-strong form of market efficiency posits that stock prices fully reflect all publicly available information, rendering fundamental and technical analysis techniques ineffective in achieving consistent above-average returns. This form encompasses a broader set of information compared to the weak form, including not only historical price data but also non-market information, such as company announcements, financial statements and accounting practices, patents held, economic reports, earnings forecasts, and industry news. This implies that neither fundamental analysis, which involves studying a company's financial performance and prospects, nor technical analysis, which relies on patterns in historical price and volume data, can consistently generate superior risk-adjusted returns.

3. **Strong form**: The strong form of market efficiency is sometimes referred to as the "perfect market theory" because it implies that markets are perfectly efficient and no investor can outperform the market consistently. This suggests that even individuals with privileged access to confidential or non-public information, such as corporate insiders or professionals with sophisticated analytical techniques, cannot exploit their informational advantages to earn abnormal profits. The strong form encompasses all available information, including what is captured by the semi-strong and weak forms, while the weak form considers the most limited set of information, namely, past prices. Researchers often begin by examining the weak form, which is the most fundamental level. If the data fails to support even the weak-form, it becomes unnecessary to test the higher levels of semi-strong and strong-form efficiency, as they would be automatically rejected.

2.1.3. Assumption of the efficient market hypothesis

The theoretical foundation for the Efficient Market Hypothesis (EMH) rest on the following assumptions:

1. **Rational Investors**: The EMH assumes that investors are rational and always make decisions aimed at maximising their expected utility or profits based on available information. Investors are assumed to be rational and value securities rationally, make unbiased forecasts of future cash flows, and discount them correctly. This presupposes that investors meticulously analyse all pertinent data and make judgments solely intended to optimise their anticipated returns or satisfaction levels.

2. **No Transaction Costs**: The EMH assumes that there are no transaction costs involved in trading securities or institutional frictions such as commission fees, taxes, or other expenses.

3. **Perfect Information**: The EMH relies on the supposition of information symmetry and instantaneous dissemination across market participants. The market processes information efficiently and adjusts security prices quickly and correctly based on new information.

4. **Homogeneous Expectations**: The EMH assumes that all investors have the same expectations about the implications of the available information on the future prices and distributions of securities.

5. **Perfect Competition**: The EMH assumes that there are many buyers and sellers in the market, and no single investor can outperform the market consistently by using any information that the market already knows (Makiel, 2003). No individual trader is large enough for their trades to affect prices (Shleifer, 2000).

6. **No Arbitrage Opportunities**: The EMH assumes that investors have no opportunities to earn risk-free profits through arbitrage, as any such opportunities would be quickly exploited and eliminated by rational investors.

7. **Efficient Market Reaction**: The EMH assumes that the market quickly and accurately adjusts security prices to reflect all relevant information, ensuring that prices always fully reflect the available information at any given time.

2.1.4 Problem with EMH

Fama (1970) states that the EMH assumes "all agree on the implications of current information for the current price and distributions of future prices of each security." Shleifer (2000) also challenges this assumption, stating that "the assumption that all investors have homogeneous expectations about the implications of available information for security returns is clearly violated in reality." Shiller (2003) critiques this assumption, arguing that "the efficient markets hypothesis is based on an assumption of homogeneous expectations among investors, which is contradicted by massive evidence of heterogeneous expectations."

Fama (1970) posits that market efficiency requires "no transaction costs in trading securities". Grossman and Stiglitz (1980) contended that this assumption is essential for the EMH to be valid. They argue that since information is costly, prices cannot perfectly reflect available information. Consequently, if transaction costs are absent, arbitrageurs will not be deterred from exploiting mispricing opportunities. However, if transaction costs are significant, the profits from exploiting mispricing may not be sufficient to cover the costs, leading to persistent inefficiencies. Thus, the assumption of no transaction costs and institutional frictions is crucial for the EMH to hold.

Kahneman and Tversky's (1979) Prospect Theory disputes the expectations of the expected utility hypothesis and rational choice-making. Shiller (2003) asserts that rationality assumptions are breached in reality, and investors exhibit herding behaviour, overconfidence, and other cognitive biases. The efficient market hypothesis posits that investors are rational and utilise all pertinent information to make investment decisions (Fama, 1970). However, the assumption that investors are rational, evaluate securities rationally, make unbiased projections of future cash inflows, and discount them correctly is disregarded in practical applications (Shleifer, 2000; Shiller, 2003). Barberis and Thaler (2003) suggested that investors exhibit cognitive biases and mental accounting that led to systematic deviations from rationality, including overconfidence, representativeness bias, and aversion to losses.

De Bondt and Thaler (1985) offer empirical evidence of investor overreaction and underreaction, contradicting the assumption of rational, unprejudiced forecasting.

Shleifer and Vishny (1997) emphasise the constraints on arbitrage, including fundamental risk, noise trader risk, and institutional constraints, which can prevent arbitrageurs from correcting mispricing. De Long et al. (1990) argued that noise traders can generate persistent deviations from fundamental values, thereby challenging the EMH. Shiller (2003) contends that the EMH's assumption of uniform expectations among investors is at odds with substantial evidence of diverse expectations. Shleifer (2000) further maintained the assumption of uniform expectations regarding the consequences of available information is not upheld in practical application.

Despite extensive research over several decades, a clear consensus on the efficiency of capital markets remains elusive. While the Efficient Market Hypothesis (EMH) has been widely accepted and heavily scrutinised, its validity continues to be a subject of ongoing debate, with empirical evidence supporting and contradicting its assumptions (Awad & Daraghma, 2009; Lim & Brooks, 2011; Yen & Lee, 2008). Numerous studies have yielded mixed results, suggesting that markets are both rationally and steadily efficient and inefficient over time (Worthington & Higgs, 2005; Borges, 2010; Gupta & Yang, 2011; Kapoor, 2017; Parulekar, 2017; Sánchez-Granero, 2020). This phenomenon has been observed across various equity markets, where researchers have provided empirical evidence of weak-form efficiency (Jain & Jain, 2013; Jansen, 2020; Jenwittayaroje, 2021; Mishra et al., 2015; Nalina & Suraj, 2013; Poshakwale, 1996), while others have rejected this hypothesis (Yadav & Arora, 2020; Khan et al., 2011; Malafeyev et al., 2019; Srinivasan, 2010). These conflicting findings underscore the complexity of market efficiency, highlighting the need for ongoing research to better understand the interplay between rational and irrational factors that influence asset prices (Baker & Wurgler, 2007; Barberis & Thaler, 2003; Daniel et al., 1998; Hirshleifer, 2001; Shiller, 2003; Timmermann & Granger, 2004; Woo et al., 2020). The impact of technological advancements, regulatory changes, and evolving market dynamics on market efficiency warrants further investigation (Ahn et al., 2020; Almail & Almuddhaf, 2017; Boehmer et al., 2021; Chordia et al., 2008; Hasbrouck, 2018; Hendershott et al., 2011; Hendershott & Moulton, 2011).

2.3. The Stock Market anomalies

The term "anomaly" has been gaining ground with prominence and broadening in the branch of economics, especially in finance. The literal meaning of an anomaly is odd or deviates from the usual occurrence. Frankfurter and McGoun (2001) defined it as an irregularity or a deviation from the normal or natural order, or an anomalous condition. Anomalies are indicators of an inefficient market, generating new, successful ideas, and more successful theories. The financial market anomalies are quite different. Initially, anomalies were used to show deviations from traditional finance in asset pricing and the efficient market; later, they were applied to new literature in behavioural finance (BF). Tversky and Kahneman (1986) defined market anomalies as "an anomaly is a deviation from the presently accepted paradigms that are too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative system".

The word ''anomaly'' has been associated with scientific and technological matters from the very beginning of its use (Kuhn, 1970). Documentation of "anomaly" is used in financial economics to refer to an irregularity, a departure from the norm, or an uncommon circumstance. That is derived from a famous work of Thomas Kuhn in his book entitled The Structure of Scientific Revolution, Kuhn (1970) provides anomalies with one answer i.e. discovery acknowledgement of anomaly, understanding that nature has in some way deviated from the paradigm-induced assumptions that underpin conventional science (Kuhn 1970, p.52). This implies that the "anomaly" exists in opposition to a "paradigm" (which often presages a transitional phase toward a new paradigm). He does not start it with a single quotation mark as he does with the terms "conventional science" and "paradigm." This implies that he has just picked what he feels as a suitable term to say what he wishes to say and does not intend to give it any unique or special meaning. As we have seen from The Oxford English Dictionary, his use of ''anomaly'' is perfectly consistent with the meanings it has had for over 400 years, and before using the word ''anomaly,'' he refers to ‘‘fundamental novelties of fact,’’ ‘‘new and unsuspected phenomena,’’ and ‘‘surprises,’’ which are apparently synonymous terms and phrases. Kuhn (1977a) makes a point on anomalies in another article he wrote concurrently with “The Structure of Scientific Revolutions, “anomalies do not emerge from the normal course of scientific research until both instruments and concepts have developed to make their emergence likely and to make the anomaly which results recognizable as a violation of expectations”. This gives the impression that anomalies are more than just the opposite outcomes that arise during typical post-positivist attempts to empirically disprove a theory, hypothesis, or model. Further, he defined anomalies as “Anomalies, by definition, exist only with respect to firmly established expectations. Experiments can create a crisis by consistently going wrong only for a group that has previously experienced everything’s seeming to go right” (Kuhn, 1977b, p. 221). Of its two general definitions, the second in The Oxford English Dictionary (1989) is ‘‘unevenness, inequality, condition, motion, etc., which can be more concerned with the financial literature. A variation of the word “anomaly” in the economic literature is dates back to 1975, in an article by Gentry (1975) titled “Capital Market Line Theory, Insurance Company Portfolio Performance and Empirical Anomalies”. His term was deferred from Kuhn's sense of financial theory. Rather, he used market data to differentiate market line theory which shows that numerous positive stock return anomalies arise compared to financial theory.

The persistence of numerous market anomalies that the EMH cannot explain has prompted academics to explore alternative theories and frameworks. The observed deviations from the assumptions of market efficiency have given rise to a crucial new field in finance: Behavioural Finance. Behavioural Finance acknowledges the presence of cognitive biases, heuristics, and irrational behaviour among market participants, which can lead to systematic deviations from rational expectations and the utility maximisation principles underlying traditional asset pricing models (Barberis & Thaler, 2003; Shiller, 2003). Behavioural Finance offers a more nuanced perspective on market anomalies, shedding light on phenomena that challenge the validity of EMH (Baker & Wurgler, 1998; Hirshleifer, 2001). For instance, the value premium anomaly, where value stocks tend to outperform growth stocks, can be attributed to the anchoring bias and the disposition effect, which lead investors to hold onto losing stocks too long and sell winning stocks too soon (Barberis et al., 2002; Frazzini, 2006). This implies that empirical evidence of market anomalies seems to contradict traditional theories of asset-pricing behaviour and also plays a crucial role in identifying potential market inefficiencies. Market anomalies indicate the existence of profit opportunities, suggesting market inefficiency or flaws in the asset-pricing models used to explain price movements (Caporale et al., 2017; Latif et al., 2011; Woo et. al., 2020).

The thesis focuses on examining the calendar anomalies and provides an in-depth analysis of this particular phenomenon in Chapter 4, which includes a comprehensive review of the relevant literature. While the existing body of research documents numerous other anomalies, this study concentrates solely on the most renowned and extensively researched calendar anomalies. The aim is not to scrutinise every anomaly recorded in the literature but to investigate the intricacies of calendar anomalies through a detailed examination and a thorough exploration of pertinent scholarly works. A discussion of some notable market anomalies that behavioural finance attempts to elucidate is as follows:

2.3.1. The Value Premium Anomaly

The value premium anomaly represents a puzzling phenomenon where value stocks, characterized by low prices relative to their fundamental indicators such as book value or earnings, tend to outperform growth stocks over extended periods (Chan & Lakonishok, 2004; Fama & French, 1992). Fama and French (1992) conducted a comprehensive study analysing the performance of stocks listed on major U.S. exchanges, including the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ, over an extensive period from 1963 to 1990. The study revealed a striking pattern: the portfolio comprising stocks with the highest book-to-market (BM) ratios, often referred to as the "value portfolio", exhibited a significantly higher monthly average return (generated an impressive monthly average return of 1.53%) compared to the portfolio consisting of stocks with the lowest BM ratios, commonly known as the "growth portfolio". Chan and Lakonishok (2004) extended their analysis to include an expanded sample of U.S. small-cap stocks and the largest stocks in the MSCI Europe/Australasia/Far East universe. Their findings reinforced the robustness of the value premium anomaly, even after accounting for the market conditions of the late 1990s. This phenomenon has been observed and consistent outperformance of value stocks relative to growth stocks has been documented in studies by Lam et al. (2019) in the Chinese stock markets from July 1995 to June 2015, Nugroho (2020) in the Indonesian stock market from 2008 to 2017, and Ho et al. (2022) in a comprehensive analysis spanning 38 countries from 1989 to 2017.

The value premium anomaly, wherein stocks with higher book-to-market (BM) ratios tend to outperform those with lower BM ratios, has been a subject of considerable research and debate. Prominent studies by De Bondt and Thaler (1987) and Lakonishok et al. (1994) proposed a behavioural explanation for this phenomenon, attributing it to investors' tendency to overreact to company fundamentals. These researchers posit that a positive correlation exists between a company's BM ratio and its underlying fundamentals, such as profitability, growth prospects, and financial health. However, investors often exhibit irrational behaviour by becoming overly pessimistic about companies with poor fundamentals and excessively optimistic about those with strong fundamentals. This overreaction leads to the mispricing of stocks, with companies having high BM ratios (typically associated with weaker fundamentals) being undervalued, while those with low BM ratios (associated with strong fundamentals) become overvalued. This empirical observation contradicts the notion of market efficiency, as it implies that investors can potentially generate higher returns by simply employing a value investing strategy (Piotroski, 2000; Hogan et al., 2004).

2.3.2. The Momentum Anomaly

Momentum anomalies refer to the empirical observation that stocks that have performed well (or poorly) over the past few months tend to continue to perform well (or poorly) over the next few months, which contradicts the efficient market hypothesis. Jegadeesh and Titman (1993) were among the first to document the momentum effect in the U.S. stock market. They construct portfolios by sorting stocks based on their past returns over the preceding six months. Remarkably, the portfolio comprising past winners yielded an average return approximately 9% higher than the portfolio of past losers over the subsequent six-month holding period. This finding was further corroborated by Chan et al. (1996), who expanded the scope of their analysis and obtained consistent results, lending credence to the robustness of the momentum effect in the NYSE, AMEX, and NASDAQ stock markets.

In the context of emerging markets, Rouwenhorst (1999) examined 20 emerging stock markets and reported significant momentum profits, with the effect being more pronounced in countries with less developed financial systems and lower market capitalization. Consistent with these findings, Chui et al., (2000) observed a strong momentum effect in the stock markets of several Asian countries, including Indonesia, Korea, Malaysia, and Thailand. Griffin et al. (2003) conducted a comprehensive analysis of momentum strategies across 42 countries spanning both developed and emerging markets. Their findings revealed that momentum strategies yielded significant positive returns in nearly all the markets examined, with the effect being particularly pronounced in emerging markets. This global presence of the momentum effect suggests that it is a widespread phenomenon that transcends geographical boundaries and market development stages.

Asness et al. (2014) offered a contrarian perspective on the momentum effect, challenging its robustness and questioning the validity of the phenomenon itself. Unlike previous researchers who sought to explain the underlying causes of momentum, they contended that the purported momentum returns are relatively small in magnitude and fragmented, raising concerns about their potential disappearance over time. Imran et al. (2020) and Cakici et al. (2013, 2016) provide mixed evidence of the momentum effect in developed and emerging stock markets. Imran's studies found a significant negative momentum effect in 13 markets, suggesting that investors cannot attain abnormal profits through momentum investing. On the other hand, Cakici's research supports the presence of the momentum effect in most emerging markets, except Eastern Europe. However, Cakici also notes that size and momentum strategies generally fail to generate superior returns in these markets. These findings suggest that, while the momentum effect may exist in some developed and emerging markets, its impact on stock returns is limited.

2.3.3. Reversal Effect/Winner–Loser Effect

The reversal effect, also known as the winner-loser effect, is an anomaly in which stocks that have previously outperformed (winners) tend to underperform in the subsequent period, while stocks that have previously underperformed (losers) tend to experience a reversal and outperform. This contradicts the efficient market hypothesis, as it suggests that stock prices overreact to information, leading to a correction and reversal in returns over longer horizons, typically three to five years. De Bondt and Thaler (1985) conducted a seminal study that provided empirical evidence for the reversal effect. Their experiment involved constructing two portfolios: one comprising the 35 stocks with the highest cumulative returns over the previous five years (winners) and the other consisting of the 35 stocks with the lowest cumulative returns over the same period (losers). They suggest that investors tend to become overly pessimistic about past loser stocks, causing their prices to become undervalued relative to their fundamentals. Conversely, investors become overly optimistic about past winner stocks, leading to overvaluation of their prices (De Bondt & Thaler, 1985, 1987).

Numerous studies, including those by (Balvers et al., 2000; Balvers & Wu, 2006), Richards, 1997; Smith & Pantilei, 2015; Spierdijk et al., 2012; Zaremba, 2016; Zaremba & Umutlu, 2018) have consistently found that markets or stocks with low past returns over the previous three to five years tend to outperform those with high past returns, contradicting the efficient market hypothesis. This reversal effect has been observed not only at the individual stock level, but also at the broader market level, suggesting a pervasive pattern of overreaction and subsequent correction in asset prices. However, recent research by Malin and Bornholt (2013) indicates that the long-term reversal effect across stock market indices may have weakened for developed countries after 1990, potentially signalling changes in market dynamics or the dissipation of this anomaly in more recent times. Kelly et al. (2021) suggest that the anomalous return patterns associated with long-term reversals can be partially explained by dynamic shifts in risk exposures, rather than solely attributed to market inefficiencies or investor irrationality. The conditional factor pricing model, which captures the evolving risk profiles of stocks based on their past return characteristics, provides a risk-based explanation for the momentum and long-term reversal phenomena, challenging the notion that these effects are purely anomalies that violate market efficiency.

2.3.4. The Disposition Effect

The disposition effect, as proposed by Shefrin and Statman (1985), refers to two behavioural tendencies. First, investors exhibit an aversion to realising losses, leading them to hold onto loss-making stocks for an extended period, even when such a course of action may be suboptimal. Second, investors eagerly sell winning stocks prematurely, driven by the desire to lock in gains and avoid potential losses, which stems from overconfidence and arrogance (Grinblatt & Han, 2005; Summers & Duxbury, 2012). A prominent explanation combines Kahneman and Tversky's prospect theory (1979) with the concept of mental accounting (Thaler, 1985) in the realm of investments. This explanation suggests that the disposition effect arises from investors' aversion to realising losses (as predicted by prospect theory) and their tendency to separate investments into distinct mental accounts, leading to a reluctance to close losing investments and propensity to sell winning investments prematurely.

Odean (1998) empirically tested this behaviour in the U.S. stock market using a random sample of 10,000 accounts from a discount brokerage house for the period 1987-1993. Their study compared the proportion of gains realised (PGR) with the proportion of losses realised (PLR). A higher PGR was observed than PLR, indicates the presence of the disposition effect. Locke and Mann (2015) conducted a study on professional futures floor traders to investigate the presence of the disposition effect, a well-documented behavioural bias in which investors tend to hold on to losing investments for too long while selling winning investments too soon (Odean, 1998; Shefrin & Statman, 1985). For instance, Grinblatt and Han (2005) found evidence of the disposition effect among mutual fund managers during the Asian financial crisis, their findings provided evidence that even professional traders are not immune to this bias. The study by Asnawi et al. (2022) on the disposition effect among Indonesian stock investors sheds light on several factors like the Covid-19 pandemic and the intensity of social media usage that influence this behavioural bias. Their findings are consistent with the existing literature on the disposition effect and offer additional insights into its prevalence and potential moderating factors. Furthermore, the disposition effect has been documented in other contexts such as real estate markets (Genesove & Mayer, 2001) and cryptocurrency trading (Haryanto et al., 2020), indicating its pervasiveness across different asset classes and market conditions.

2.3.5. The Bubbles effect

The bubble effect in the stock market can be defined as the process by which the overpricing and speculative behaviour originating in a specific sector or group of stocks eventually permeates other sectors and the broader market. The unprecedented rise in stock prices of high-technology firms during the late 1990s and early 2000s led to the formation of a speculative bubble, commonly known as the "dot-com bubble." This bubble was characterised by a significant overvaluation of Internet-based companies and other technology firms, driven by over-optimistic expectations and excessive speculation. The seminal study that reported the occurrence of bubbles in experimental asset markets was conducted by Smith et al. (1988). This study provides empirical evidence of speculative bubbles forming in controlled laboratory settings, challenging the traditional assumptions of market efficiency and rational behaviour. In their experimental design, Smith et al. (1988) created a controlled environment where participants traded an asset with a known fundamental value. All investors received the same dividend from a known probability distribution at the end of each trading period, which lasted for either the T=15 or T=30 period. The experiments revealed that 14 of the 22 trials exhibited the formation of price bubbles, characterised by a substantial deviation of market prices from the asset's intrinsic dividend value, followed by a subsequent crash. The bubble phenomenon observed in these experiments can be interpreted as a form of temporary myopia, a concept proposed by Tirole (1982). Evans (1991) and Charemze and Deadman (1995) highlight the periodic behavior of market bubbles, suggesting that asset prices tend to experience significant deviations from their fundamental values during certain phases, which are subsequently followed by periods of correction as prices revert to more rational levels.

Shiller (1999) utilised the foundations of behavioural finance to predict a substantial collapse in stock prices, which later became known as the tech bubble. In line with an earlier study, Shiller (2001) argued that the stock market exhibited signs of irrational behaviour and speculative excesses, particularly in the technology sector. He employed valuation metrics such as the dividend-to-price ratio and the price-to-earnings (P/E) ratio to demonstrate that stock prices had become disconnected from their fundamental values. Empirical evidence supporting the existence of speculative bubbles in equity markets has been documented across various contexts. Bhar and Malliaris (2006) demonstrated that speculative bubbles in U.S. markets subsequently precipitate similar phenomena in other mature financial markets, suggesting a contagion effect in global asset valuations. Similarly, Mirza and Afzal (2012) identified speculative components within the emerging Karachi Stock Exchange, extending the understanding of bubble formation beyond established markets. Moreover, Junttila and Kinnunen (2004) detected speculative elements specifically within the information technology sector of the Finnish stock market. Blanchard and Raymond (2004) conducted a study to examine the speculative bubble hypothesis in major stock markets, including France, Germany, Japan, the United Kingdom, and the United States from 1973 to 2002, employing cointegration tests corrected for skewness and excess kurtosis, suggesting the presence of speculative bubbles in these markets. Brunnermeier (2016) provides a comprehensive review of the theoretical and empirical literature on asset price bubbles, covering different models and approaches to understanding the causes and dynamics of bubble formation and collapse. The result highlights that bubbles can emerge even in settings without the theoretical prerequisites, such as asymmetric information, limits to arbitrage, and heterogeneous beliefs combined with short-sale constraints can all lead to the emergence and persistence of asset price bubbles. Zeren and Yilanc (2019) provided empirical evidence in detecting multiple bubbles in 15 countries, with these bubbles occurring before local and global crisis periods. However, Gupta et al. (2023) highlights those shocks on the bubble indicators for BRICS countries appear to be relatively modest.

This finding suggests that these specific economies experienced substantial deviations from their long-term equilibrium trends, potentially signalling the presence of asset price bubbles or imbalances in the medium and short term. A similar finding was reported by Eyden et al. (2023) in G7 countries.

2.3.6. Herd Effect Anomaly

Herd behaviour, a phenomenon where individuals mimic the actions of others, can contradict the assumptions of the efficient market hypothesis (EMH). Herd behaviour imitates the crowed behaviour, instead of following his own beliefs and information, rather sticks to mass trading decision and also cause informational inefficiency in the market (Cipriani & Guarino, 2014). Empirical evidence also supports the existence of herd behaviour in financial markets. Studies have shown that institutional investors tend to follow the trades of other institutional investors, particularly during periods of high market volatility or uncertainty (Lakonishok, et al., 1992). Similar finding was reported by Li et al. (2019) who provide empirical evidence that herd behaviour in the Chinese A-share market is more pronounced during periods of market turmoil, particularly when the market experiences downward movements. The herd behaviour is relatively more profound in emerging market (Chiang & Zheng, 2010; Komulainen, 2001). When the stock market moves in an extreme condition like crisis, investors loss their confidence and tend to follow the other investors due to intrinsic preference for conformity (Bikhchandani & Sharma, 2001). Dang and Lin (2016) found evidence herb behaviour when the share price increased. Herding is more prevalent in open ended funds as compared to closed ended funds (Borensztein & Gelos, 2003). Chauhan, et al., (2020) examined the effect herding behaviour in small and large cap stock in National stock exchange and found that stocks with large capitalisation of stock are less prone to herding. Moreover, Lyu et al., (2021) found that heightened herd behaviour during the COVID-19 pandemic led to a shift in power dynamics between individual and institutional investors, resulting in increased market volatility.

2.3.7 The Size effect

Banz’s seminal work in 1981 revealed an intriguing phenomenon known as the “size effect.” This effect suggests that the size of a firm and the return on its common stock are inversely related. In other words, smaller stocks (with lower market capitalization) tend to exhibit higher average returns (Reinganum, 1981). This finding challenges the Efficient Market Hypothesis (EMH), particularly when considering the arrival of January, which is typically regarded as public information (Siegel 1998). Additionally, Brown et al. (1983) and Keim, (1983) conducted studies on NYSE and AMEX firms, emphasizing their inherent risks and unique characteristics. Their findings suggest that small firms have higher beta than large firm. Lakonishok et al. (1994) found that stocks with higher price-to-earnings (P/E) ratios, typically deemed riskier, paradoxically exhibited lower future returns. Conversely, companies with higher book-to-market (BM) ratios tended to generate higher returns. Numerous studies have investigated the extent of the size effect; Chan et al. (1991) in Japan, Rouwenhorst (1999) in Emerging markets, Bagella et al. (2000) in United Kingdom, Liu et al. (2019) in China, Pandey et al. (2019) in Europe, Pandey and Segal (2016) in India and among other consistently demonstrated that smaller firms tend to generate superior returns compared to their larger counterparts. This empirical regularity, often referred to as the size premium, exhibits a remarkable degree of consistency across diverse global equity markets

Daniel and Titman (1997) argued that these factors merely reflect investor preferences rather than being intrinsic drivers of returns. Crain (2011) found that the size effect has diminished since the 1980s, with variations attributed to factors like market liquidity. In the context of concrete structures, Elfahal (2002) highlighted the need to consider the size effect in design, particularly in high-strength concrete and under dynamic loading. Qiu et al. (2017) discussed the challenges posed by the size effect in micro-forming, where material deformation behaviour changes at the micro level. The size effect contradicts the EMH's assumptions of market efficiency, its consistent observation across various markets and time periods underscores its significance as a persistent of size effect phenomena in stock market.

2.2.8 The Calendar Anomalies – Day of the week, month of the year, turn of the month

Calendar anomalies refer to the observed patterns or regularities in stock returns that are related to specific calendar periods, defying the efficient market hypothesis (EMH). These anomalies suggest that stock returns exhibit predictable tendencies, either higher or lower, depending on factors such as the day of the week, the day of the month, or the month of the year. The origins of calendar anomalies can be traced back to the 1930s, Kelly (1930) found that Monday is worse day to buy a stock. Cross (1973) was the first to conduct academic study that took in to account for the fact that Monday effect tend to show the lowest stock returns as compare to other days.

Another type of anomaly in the literature is month-of-the-year anomaly. The earliest documented reference to a month of the year effect is credited to Wachtel (1942), who observed the "January effect" – the tendency of stock prices to rise more in January than in other months, particularly for small-capitalization stocks. The well-known study on the month-of-the-year effect conducted by Rozeff and Kinney (1976) gained attention from practitioner and academics. They found that average stock returns in the NYSE were significantly higher in January (3.48%) compared to other months of the year (0.42%). The tax-loss selling hypothesis has been widely accepted as a theoretical explanation for the January effect. This hypothesis suggests that investors engage in tax-loss selling towards the end of the year to realize losses for tax purposes. Subsequently, they rebalance their portfolios in January, which contribute to the observed higher stock returns during that month (Dahlquist & Sellin, 1994; Ritter, 1988).

Another anomaly observed in financial markets is the turn-of-the-month effect, also known as the month-end effect. This anomaly refers to the tendency for stock prices to exhibit higher returns around the turn of the month, specifically during the last trading day of the current month and the first few trading days of the following month. Ariel (1987) in a seminal study on the US stock market exhibited persistent and statistically significant outperformance compared to the returns for the entire month. Lakonishok and Smidt (1988) corroborated the existence of the turn-of-the-month effect and proposed that it could be linked to the timing of monthly salary payments and the subsequent reinvestment of funds by individual investors. Several studies in market anomalies like Narayan and Zheng, (2010) in Chinese stock market, Farag (2013) in Emerging market, Deyshappriya (2014) in Colombia stock exchange, Ahmed and Boutheina (2017) in Tunisia stock market provides an evidence of market anomalies in calendar effect across different stock market. Meanwhile, Rossi and Gunardi, (2018) did not found strong evidence of calendar effect. Market anomalies do not occur all time (Chalamandaris et al., 2021). Other studies also suggest that these market anomalies do not occur all the time but to a large extend, do appear periodically (Engelberg et al., 2018; Wahal, 2019) and among others.

Numerous research studies have investigated the phenomenon of calendar effects in financial markets over the years. Table 2.1 provides a chronological overview of the various studies that have explored and established various calendar anomalies. The detail discussion is provided in chapter 4. Empirical research on calendar anomalies has been conducted across global financial markets. However, the findings regarding these market anomalies have been mixed, with no clear consensus emerging from the diverse techniques and approaches employed by researchers. Despite extensive investigation, the existence and persistence of calendar effects remain a topic of ongoing debate within the academic literature.

Table 2.1: Chronological representation of various studies conducted in calendar effects

Calendar anomalies	Studies conducted
Day of the Week Effect	(Osborne, 1962; Cross, 1973; Gibbons & Hess, 1981; Jaffe & Westerfield, 1985; Wong & Ho, 1986; Wong et al., 1992; Cheung & Hu, 1997; Steeley, 2001; Kamath & Chusanachoti, 2002; Bildik, 2004; Basher & Sadorsky, 2006; Stavarek & Heryán, 2012; Chia, 2014; Cinko et al., 2015; Olson et al., 2015; Chatzitzisi et al., 2019; Gkillas et al., 2020; Komariah & Ramadhan, 2022)
	(Rozeff & Kinney, 1976; Gultekin & Gultekin, 1983; Berges et al., 1984; Reinganum & Shapiro, 1987; Ritter,

Month of the year	1988; Aggarwal & Rivoli, 1989; Ignatius, 1992; Agrawal & Tandon, 1994; Haugen & Jorion, 1996; Choudhary, 2001; Bouman & Jacobsen, 2002; Ciccone & Etebari, 2008; Alrabadi & Al-Qudah, 2012; Alagidede, 2013; Mangala & Lohia, 2013; Wang et al., 2013; Dichtl & Drobetz, 2014; Wen & Li, 2016; Rossi & Gunardi, 2018; Bajaj et al., 2019; Plastun et al., 2020; Agarwal & Jha, 2023; Acharya et al., 2024)
Turn of the month	(Ariel, 1987; Lakonishok & Smidt, 1988; Cadsby & Ratner, 1992; Agarwal & Tandon, 1994; Horowitz et al., 1999; Maberly & Waggoner, 2000; Kunkel et al., 2003; McConnell & Xu, 2008; Liu, 2013; Vasileiou, 2013; Sharma & Narayan, 2014; Kumar, 2015; Kayacetin & Lekpek, 2016; Caporale & Plastun, 2017; Aziz & Ansari, 2017; Khan & Rabani, 2018; Arendras & Kotlebova, 2019; Singh et al., 2020)

Source: Author compilation

2.4. Trading Rules and Technical Analysis

Technical analysis, the study of historical market data to identify patterns and forecast future price trends, has a rich history spanning several centuries (Murphy, 1999). Its origins can be traced back to the 16th and 17th centuries, when Dutch and Japanese rice traders analysed price charts to detect emerging trends (Pring, 2014). One of the earliest known works on the subject, "Confusión de Confusiones" by Joseph de la Vega (1688), described price movements and patterns observed in the Amsterdam stock exchange. A significant milestone was the introduction of the Dow Jones averages by Charles Dow in 1884, which laid the foundation for modern technical analysis by tracking market movements (Rhea, 1994). In 1924, Richard Schabacker's "Technical Analysis and Stock Market Profits" outlined various charting techniques and patterns, further contributing to the field's development (Schabacker, 1932). Park and Irwin (2007) note that a form of technical analysis specifically the candlestick charting, was introduced by the Japanese as early as the 18th century, though it wasn't introduced to the West until the 1970s. Technical analysis pioneers like Murphy (1999), DeMark (1997) and Pring, (2014) made significant contributions to developing and popularizing various techniques and indicators. Despite debates around its efficacy, the core principles of analysing price movements to identify trends and patterns remain integral to technical analysis. It continues to be widely employed alongside other analytical methods by traders and investors globally.

The buy-and-hold strategy, which involves purchasing an asset and holding it for a prolonged period, has been extensively studied in academic literature. Several studies have found evidence supporting the long-term outperformance of buy-and-hold strategies, particularly in well-functioning and efficient markets (Malkiel, 1995; Bogle, 1999). These studies argue that over longer time horizons, the buy-and-hold approach tends to outperform more active trading strategies due to the compounding effect of returns and lower transaction costs. Lohpetch & Corne (2010) document that the daily weekly and monthly buy-and-hold strategy is possible to outperform the returns to beat the market. Hui and Chan (2018) developed an alternative approached to buy-and-hold, the generalized time-dependent trading strategy and evaluated its performance on 12 stock indices. Their findings revealed a mixed result, indicating that the generalized time-dependent strategy outperformed buy-and-hold approaches in certain markets, but failed to consistently deliver superior returns across all the indices examined. However, other researchers have documented periods and market conditions where buy-and-hold strategies underperform compared to more active trading strategies, such as moving average and trading range break approaches (Brock et al., 1992; Sullivan et al., 1999). Hui and Chan (2019) proposed two alternative trading strategies aimed at outperforming buy-and-hold approaches. Their research reinforces the notion that the relative performance of buy-and-hold strategies can fluctuate based on factors such as market conditions, asset classes, and time periods. This underscores the potential for investors to devise more sophisticated trading strategies to enhance profitability in today's globalized financial markets.

Filter rules, also referred to as implied trading strategy are another popular category of technical analysis rule that aims to filter out smaller price fluctuations and identify significant trend changes. These rules involve setting trailing stop-loss or profit-taking levels based on the current price trend. Several studies have found evidence supporting the ability of filter rules to generate significant returns in various markets, particularly in trending market conditions (Fama & Blume, 1966; Brock et al., 1992; Sweeney, 1988). These studies suggest that filter rules can outperform buy-and-hold strategies by capturing larger price movements while minimizing exposure to smaller, potentially noisy fluctuations. However, other researchers have questioned the robustness of these findings, arguing that the apparent profitability of filter rules may be due to data snooping biases, transaction costs, or risk factors not properly accounted for (Park & Irwin, 2007; Qi & Wu, 2006; Sullivan et al., 1999).

Given the extensive array of technical rules documented in the literature, a comprehensive examination of all trading rules falls beyond the scope of this thesis. Instead, the focus is directed specifically toward the buy-and-hold trading strategy outperforming the implied trading strategy, which is explored in Chapter 4 with in-depth analysis and evaluation of the existing body of research pertaining by comparing the buy-and-hold trading strategy and implied trading strategy.

2.5. The Sentiment of Investors

Investor sentiment has gained significant attention in financial market research, with academics exploring its impact on stock returns, market volatility, and its measurement and incorporation into financial models. People's sentiments encompassing feelings, thoughts, attitudes, emotions and ideas about a situation play an important role in investors' opinions (Mittal & Goel, 2012). Early research suggests that the formation of speculative bubbles (Smidt, 1968), the development of biased expectations among market participants (Zweig 1973), and the presence of noise in financial markets (Black 1986), "expectations of market participants relative to a norm" (Cliff & Denis, 2004) and wave of optimism and pessimism (Baker & Wular, 2006) were linked with sentiment.

Academics believe that investor sentiment has the potential to influence stock market returns, and existing literature concentrates on the impact of sentiment on both returns and volatility. Wysocki (1998) investigated the factors influencing the web posting volume of messages on stock message boards and the impact on stock trading volume and return. He found that the volume of messages posted during off-market hours can serve as a predictor for fluctuations in both trading volume and stock returns on the following trading day. Similar studies have also found empirical evidence suggesting a correlation between investor sentiment and stock prices (Antweiler & Frank, 2004; Das & Chen, 2007; Tumarkin & Whitelaw, 2001). Fisher and Statman (2002) demonstrated that investor sentiment, as measured by survey data, is positively associated with contemporaneous stock returns. A similar finding was found by (Brown and Cliff (2004) and Schmeling (2009). Similarly, Baker and Wurgler (2006) constructed a proxy of sentiment index based and found that higher sentiment leads to higher current monthly returns, particularly for stocks that are more difficult to value and arbitrage. In addition to the impact of investor sentiment on stock returns, several studies have also focused on how sentiment influences stock market volatility. For instance, De Long et al. (1990) proposed the "noise trader" model, which suggests that sentiment-driven investors can create additional risk in the market, leading to increased volatility. Lee et al. (2002) found that changes in investor sentiment (American Association of Individual Investors) sentiment index, are positively related to market volatility. Johnston and Nedelescu (2005) found market volatility and market uncertainty due to major disruption in examining the reaction in the market to the 9/11 terrorist attack in the US. Wang et al. (2006) conducted a study on the relationship between investor sentiment and stock market volatility using various sentiment proxies like the American Association for Individual Investors (AAII) and Investor Intelligence (II). They found that sentiment has a significant positive effect on volatility when investors are more pessimistic.

Researchers have explored various factors influencing stock market fluctuations, including fundamental news (Cutler et al., 1989; Li et al., 2014; Sundaram, 2020), macroeconomic variables (Humpe & Macmillan, 2009; Luís et al., 2021), political events (Bialkowski et al., 2008), natural disasters (Akter et al., 2023; Angbazo & Narayanan 1996; Lamb 1995,1998; Shan & Gong 2012; Worthington & Valadkhani, 2004), and even sports outcomes (Edmans et al., 2007). Studies have also found that natural phenomena such as cloud cover (Saunders, 1993), daylight (Kamstra et al., 2000; 2003), sunshine (Hirshleifer & Shumway, 2003), and temperature (Cao & Wei, 2005) can impact stock market sentiment and movement. More recently, the sentiment towards the COVID-19 pandemic has been shown to play a significant role in global market dynamics. A series of studies have explored the relationship between the investor sentiment in extreme circumstances. Urquhart (2013) found that there was strong negative investor sentiment during World War-II in Britain. Gong et al. (2016) further supported this, showing that extreme returns can significantly impact investor sentiment, particularly in pessimistic situations. Piccoli and Chaudhary (2018) added to this by demonstrating that investor sentiment can drive overreactions to extreme market events, with stronger overreactions occurring when sentiment is low. Mushinada (2020) expanded the discussion by highlighting the simultaneous existence of rationality and cognitive biases in individual investors, suggesting that they are adaptable to market dynamics. Despite the extensive research on investor sentiment and its impact on financial markets, there is a notable lack of comprehensive studies examining the specific influence of extreme shocks like natural disasters on stock market returns and the associated public sentiment. Investigating the precise mechanisms through which disasters alter perceptions, risk attitudes, and sentiment related to financial markets could provide new insights into market dynamics and pricing following such environmental shocks. This topic is explored in more detail in Chapter 5.

2.6. The Adaptive Market Hypothesis

The Adaptive Market Hypothesis (AMH), proposed by Andrew Lo in 2004, can be considered an evolutionary extension of the Efficient Market Hypothesis (EMH). It is derived from biological perspective and incorporates insights from behavioural finance (Lo, 2004). Lo (2004) states “Price reflects as much information as dictated by the combination of environmental conditions and the number and nature of species in the economy”. In his 2005 work, "Reconciling efficient markets with behavioural finance: The adaptive markets hypothesis," Lo further developed AMH, which he had initially proposed in 2004 and posits that market efficiency is not a fixed state but rather a dynamic process that evolves over time, driven by the principles of evolution: competition, mutation, reproduction, and natural selection (Lo, 2005).

Further, Lo (2005) states the financial market is grounded in evolutionary principles (Anderson, 1994; Nelson & Winter, 1982), and the dynamic ecology of market factors (Farmer & Lo,1999; Farmer 2002). According to Lo, the degree of market efficiency is dynamic, depending on the environment of market factors such as competitors, the availability of profit opportunities, and adaptability of market participants.

The fundamental idea of AMH is that the financial market relies on both rational and irrational behaviour (Lo, 2004). This implies the risk and reward system changes overtime due to shifts in preferences of market participants. The AMH incorporates the concept of "survival of the richest", suggesting that the strategies and behaviours that prove most successful in a given market environment are more likely to persist and be adopted by others (Brennan & Lo, 2011). The change market conditions (Charles et al., 2012; Lo, 2005) provides that profit opportunities are being constantly created and disappear. Moreover, Past prices impact current preferences due to natural selection, contrasted with a weak form of efficiency where price history is irrelevant. The market efficiency is context-dependent and subject to evolutionary forces (Lo, 2012). Behavioural biases in finance align with an evolutionary model of individuals adapt to a changing environment. These biases reflect the impact of evolutionary forces on financial institutions. The evolutionary process (AMH) argues that the degree of market efficiency can vary over time and across markets, depending on factors such as the number of competitors, the magnitude of profit opportunities, and the adaptability of market participants (Lo, 2004; Neely, et al, 2009). Moreover, Arbitrage opportunities exist in an adaptive market.

2.6.1 Principles of the AMH

Lo (2005) outlines the following key principles of the AMH:

1. Market participants act in their own self-interest, striving to maximize their individual benefits.
2. Human beings are prone to making mistakes and exhibiting biases in their decision-making processes.
3. Market participants learn from their experiences and adapt their strategies accordingly to improve their performance over time.

4. Competition among market participants drives innovation and adaptation, as they continuously seek to gain an advantage over others.
5. The natural selection process shapes the overall market ecology, favouring strategies and participants that are better suited to the prevailing market conditions.
6. Market dynamics are ultimately determined by the evolutionary forces of competition, adaptation, and natural selection, which collectively shape the behaviour of market participants and market efficiency.

2.6.2 Implication of AMH

The principles have several practical implications for the field of finance. One of the key implications pertains to the decision-making process for asset allocation. Unlike the traditional view of stable market movements over time, the AMH suggests that the risk-reward relationship in financial markets is dynamic and subject to change (Lo, 2005). Secondly, The AMH proposes a more intricate set of market dynamics characterized by cycles, trends, and various psychological phenomena such as fear, manias, bubbles, and crashes. These complex dynamics, which are commonly observed in real-world markets, create opportunities for investors to capitalize on market inefficiencies (Brennan & Lo, 2011). As a result, arbitrage opportunities do arise over time. A strategy that performs well in one market environment may not necessarily maintain its success in a different market context. This suggests that the profitability of arbitrage opportunities can vary over time, with periods of decline followed by resurgences. The third implication is that the success of investment strategies is dependent on the prevailing market environment. The AMH suggests that characteristics like value and growth may behave as risk factors, but their impact on portfolio returns can fluctuate over time. While a portfolio may generate expected returns during specific periods, the risk factors driving those returns are not necessarily constant. Moreover, the characteristics of asset prices may be influenced by the composition of the investor population at any given point in time. The fourth implication suggests that investment strategies are not consistent across different market environments. A strategy that yields favourable results in one setting may lead to subpar outcomes in another (Lo, 2004). This implies that the success of an investment strategy is contingent upon the prevailing market conditions and that arbitrage opportunities may emerge and dissipate over time (Lo, 2005). Lo (2005) demonstrates this concept by analysing the rolling first-order autocorrelation of monthly returns of the S&P Composite Index from January 1871 to April 2003. The study reveals that the degree of market efficiency fluctuates cyclically over time. Notably, there were periods in the 1950s when the market exhibited greater efficiency compared to the early 1990s (Lo, 2005).

2.6.3 Studies related to AMH

The AMH has been the subject of increasing attention in recent academic literature. Lim et al. (2006) investigated the dynamic nature of market efficiency in 10 developing stock markets by employing the portmanteau bicorrelation test statistic with fixed-length rolling windows and found that the degree of nonlinear predictability exhibited by various return series evolves dynamically over time, rather than remaining constant. Similar results were found by Todea et al., (2009) using linear and nonlinear tests for a sample period from 1997-2008 in the European stock market. They further claimed that linear and nonlinear correlations appear to follow episodic or cyclical patterns which is consistent with Lo's (2005) postulation. Similarly, Neely et al. (2007) explored the AMH by examining the declining returns on trading rules over time. They argue that if the returns decline at a sufficiently slow rate, it provides evidence in support of the AMH. The gradual decline in returns implies that market participants adapt to the changing market environment, leading to a reduction in the profitability of trading strategies. This notion is further supported by (Timmermann & Granger, 2004), who show that the performance of forecasting models varies over time due to the evolving nature of financial markets. Further, Butler and Kazakov (2012) employed various computational intelligence techniques, including GARCH, Adaptive Bollinger Bands (ABBs), and Particle Swarm Optimization (PSO), over nine years from 2001 to 2010. Their findings reveal that the market exhibits nonlinear dependence and cyclical predictability that advance to profitability over the sample period utilized. Ito and Sugiyama (2009) investigated the efficiency of the U.S. stock market using autocorrelation and state space models. Their findings indicate that market efficiency varies over time, with the U.S. market exhibiting inefficiency during the late 1980s and higher efficiency around 2000 and in the latter half of the century. The study also highlights that market crashes, bubbles, and economic and political crises influence return predictability, leading to uncertainty in market predictability during such events. Similar findings have been reported by Kim et al. (2011) and Lim et al. (2013).

Recent studies in developed countries have demonstrated time-varying predictability. These studies in US, UK and Japanese Stock markets (Urquhart & Hudson, 2013), European Union Stock market (Sensoy & Tabak, 2015), Japanese stock market (Noda, 2016), US, UK, Japan and Euro stock exchange (Urquhart & McGroaty, 2016), French stock exchange (Boya, 2019; Enow, 2022), and NYSE (Shahid et al., 2020) suggested time-varying predictability and the market can be best described as conforming to the AMH. Moreover, various studies in emerging and frontier markets suggest evidence supporting the AMH as a better explanation of market behaviour: Evidence for time-varying predictability and the Adaptive Market Hypothesis has been documented across various emerging and frontier markets. These includ Montenegro equity market (Popović et al., 2013); Indian stock market (Hiremath & Kumari, 2014); Tehran Stock Exchange (Ghazani & Araghi, 2014); Pakistan Stock Exchange (Sahid & Sattar, 2017); Ghana Stock Exchange (Gyamfi, 2017); the Chinese A-share stock market (Zhu, 2017); Chinese stock market (Xiong et al., 2018); Nigerian stock market (Ndubuisi & Okere, 2018; Adaramola & Obisesan, 2021); Vietnamese stock market (Trung & Quang, 2019); Tunisia Stock Market (Obalade & Muzindutsi, 2020); Borsa Istanbul (Burhan & Eylem, 2021); Moroccan stock market (Lekhal & Oubani, 2020); South African market (Munir et al., 2022). These findings collectively suggest market inefficiencies in certain periods, they show a discernible progression toward efficiency, consistent with the Adaptive Market Hypothesis (AMH). However, emerging markets are not fully adaptive, but move towards efficiency; overall, there is a discernible degree of market efficiency.

Despite the growing body of literature on AMH, there is a notable gap in research concerning the evaluation of time-dependent returns with the AMH framework, particularly in comparing emerging and developing countries. Sensoy and

Tabak (2015) argue that the adaptive behaviour of stock markets can manifest differently across countries, suggesting that the implications of AMH may vary depending on the specific market context. This notion is further supported by (Tripathi & Dixit, 2020), who emphasises that markets can differ significantly in terms of their geographical location, operational characteristics, and the size of their respective economies. These differences can lead to unique patterns of market efficiency and adaptability, highlighting the need for comparative studies that examine the AMH across diverse market settings. To address this research gap, the current study aims to investigate the dynamic market assumption of the AMH by examining time-dependent returns in a comparative analysis of emerging and developing countries. Chapter 3 provides a more in-depth discussion of the relevant studies.

CHAPTER 3: An Examination of Time Dependent Stock Return on BRICS and G-5 Countries: A Comparative Analysis

3.1. Introduction

The behaviour and patterns of stock market returns have remained a significant area of focus for researchers, regulatory bodies, and industry professionals. Academic scholars have dedicated substantial efforts and resources to study and comprehend the dynamics of security prices over various periods. Their efforts aimed to explain the underlying factors and mechanisms that influence the fluctuations and trends observed in the stock markets. The efficient market hypothesis (EMH) relates to the independent nature of price changes (Kendall, 1953; Osborne, 1962; Samuelson, 1956), and the absence of predictability in stock returns (Fama, 1965, 1970) provides several interesting and empirically testable predictions regarding the behaviour of financial asset prices and returns. Traditional research on the behaviour of security prices has predominantly relied on linear modelling techniques for analysis. However, as acknowledged by Fama (1965), these linear approaches have some inherent limitations. They lack the sophistication to capture the intricate patterns that technical analysts, known as chartists, claim to identify within stock price movements. This chapter focuses on both linear and nonlinear tests to examine the time-dependence of stock returns. As linear models employed may not be sufficiently advanced to unknot the complex dynamics and nuances that chartists assert exist in the fluctuations of stock prices over time.

Several studies have highlighted the time-dependent nature of stock returns, challenging the traditional assumption of constant parameters (Enow, 2023**;** Kullmann, 2002; Lo & MacKinlay, 1990**).** This time dependence has been further explored in the context of long-range dependence, with the presence of a predictable component suggesting a departure from the efficient market hypothesis (Odonkor et al., 2022). The presence of this time-dependent pattern in stock returns implies that past information can potentially be leveraged to enhance the predictability of future returns. This chapter aims to comprehensively examine a series of tests designed to detect time dependence to gain a thorough understanding of how stock prices behave over time. For this purpose, the study employed a comprehensive set of tests to rigorously examine time-dependent tests and the potential predictability of stock returns. The traditional serial correlation test examines the correlation between the price changes. In addition to the traditional serial correlation test, the variance ratio test is used to detect serial correlations in the return series that account for the heteroscedasticity properties in stock returns. Nonlinear dependence is investigated through pre-whitening procedures using AR(p) and AR-GARCH filters, followed by McLeod-Li, Engle's LM, and BDS tests. To address the issue of nonlinear heteroskedasticity in returns, an AR-GARCH filter was applied, and a BDS test was conducted on the filtered returns.

The primary objective of this study in this chapter is to investigate the presence of time dependence and stock price return predictability in the BRICS (Brazil, Russia, India, China, and South Africa) and G5 (United States, United Kingdom, France, Germany, and Japan) countries. By examining these two distinct groups, the study compares the evidence supporting the Adaptive Market Hypothesis (AMH) in developed (G5) and developing (BRICS) economies. To capture the dynamic nature of stock return behaviour over time, the data are divided into three-year subsamples. This approach allows for an assessment of how the stock returns evolve and potentially exhibit varying patterns across different periods. The study seeks to categorise the behaviour of each market under the various tests employed, based on the suggested classification of markets (Urquhart, 2013). This categorisation will facilitate a more nuanced understanding of market dynamics and potential adherence to or deviations from the efficient market hypothesis across the BRICS and G5 countries.

3.2. Review of Literature

Earlier empirical evidence shows that stock price changes appeared to be random and independent and found a degree of serially uncorrelated in the stock returns (Cowles & Jones, 1937; Fama 1965; Kendall, 1953, Osborne 1962; Samuelson 1956). Kendall (1953) presented a pioneering paper that examined the behaviour of stock and commodity prices in search of regular cycles. The results reveal the existence of such regular price cycles; instead, the series of outcomes resembled serially uncorrelated in commodities market and share prices followed a Markov process. Cowles and Jones (1937) examined the forecasting abilities of 45 representative financial agencies regarding common stock prices. Their findings indicated a notable serial correlation in the average time-series indices of stock prices. However, Alexander (1961) challenged their findings, attributing them to "spurious correlation", resulting from using monthly averages instead of monthly values. Cootner (1962) presents evidence challenging the hypothesis by demonstrating that a specific decision rule could outperform randomly purchased stocks. Additionally, Alexander (1964) addressed the criticisms of his previous 1961 paper and concluded that the S&P Industrials Index did not follow a random walk pattern. Samuelson (1965) provided a theoretical framework using a rigorous mathematical and economic foundation for randomness in stock price movements that act as the cornerstone of the EMH. These findings raise questions about the validity of the random walk hypothesis and the efficiency of stock markets, fuelling ongoing debates and further research in the field.

Recently, testing EMH in return predictability using serial correlation has also been utilised in the literature. Gilmore and McManu (2003) conducted a study on the central European market for the period–1989-1995 using daily and weekly returns to investigate whether the central European markets are efficient. They suggest that random behaviour or return independence was found in Czech Republic, Hungary, and Poland markets. Similarly, (Worthington & Higgs, 2005) conducted a comparative analysis of the emerging and developing Asian equity markets using daily stock returns. They found that the market can be categorised as time-varying return dependence and independence. Hong Kong, New Zealand, and Japanese markets are found to follow a random walk behaviour in the market and are considered independent in stock price movement, and the rest of the markets are found to be inefficient due to serial correlation in the return series. Borges (2010) conducted a study of six major European stock markets to examine weak-form efficiency using serial correlation. The results of the monthly data suggest that European markets are efficient. However, Hamid et al. (2017) conducted a similar approach in the Asia-Pacific market and found that monthly prices do not follow a random walk in all Asian Pacific countries. Recent studies in various countries using autocorrelation have suggested distinct levels of market efficiency. (Dhankar & Dhankar, 2019; Jain & Jain, 2013) suggested high degree of serial correlation daily closing price of Indian stock exchange market and inefficient market. Ferreira and Dionisio (2016) found significant correlation coefficients up to the 149th lag length equivalent to 7-month period that contradicts the EMH. Firoj and Khanom (2018) found that the Bangladeshi stock market is weak-form efficient, and independent behaviour of stock return predictability is observed in socially responsible indices. The findings of Hawaldar et al. (2017) on the Bharian stock market, which revealed significantly low to moderate levels of both positive and negative autocorrelation, suggest that the market does not conform to the traditional definition of an efficient market. However, Umoru et al. (2020) find that the predictability of stock returns does not depend on the past performance of the stock, and the stock price is fundamentally random in the frontier. The study by Ehiedu and Obi (2022) revealed that the assessment of market efficiency yields mixed results depending on the timeframe and testing methodology employed. Their findings indicated that when analysing the data on a monthly basis, the market exhibited characteristics consistent with efficiency, whereas the yearly data suggested inefficiency. This inconsistency in the results highlights the sensitivity of market efficiency tests to the choice of time intervals and methodological approaches (Hossain et al., 2020). This lack of a clear definition of market efficiency raises questions about the applicability of the EMH in different market contexts, and the need for alternative frameworks and extensive studies comparing various markets is required to understand market dynamics (Lim & Brooks, 2011; Lo, 2004).

Based on the literature discussed above, it can be conjectured that developed markets exhibit a higher degree of dependence on historical information for predicting stock returns than developing markets. This conjecture suggests that stock prices in more mature and established markets tend to follow patterns that can be exploited for forecasting purposes, whereas stock prices in emerging or developing markets may display greater unpredictability and irregularity.

The study in market efficiency also generally employed variance ratio test after the seminal paper developed by Lo and Mackinlay (1988). Karemera et al. (1999) tested the predictability of 15 emerging market returns for a period of 1986 to 1995 using variance ratio and multiple variance ratio. They found that ten of the 15 countries showed return independence, random behaviour was found using a multi-variance ratio, and six out of the total sample provided random behaviour in the emerging market. This implies that random behaviour varies among countries. The same result was obtained by Kim and Shamsuddin (2008), who used multiple variance ratio tests in Asian countries. Hoque et al. (2007) examine the return dependence of stock return of eight emerging equity markets among Asian countries. They found that most markets are mean-reverting and weak-form efficient, except in Taiwan and Korea, suggesting an alternative variance test for more accurate results. Hung et al. (2009) investigated the validity of the weak-form efficiency on TOPIX and FTSE markets by employing parametric and non-parametric variance ratio (VR) tests on large- and small-capitalization stock indices. The sample period for the TOPIX is 1 January 1993 to 17 October 2005 and 1 January 1986 to 17 October 2005 for the FTSE. They documented that large-cap stock indices exhibited characteristics consistent with market efficiency, and small-cap indices displayed pricing inefficiencies, suggesting that these indices might contain exploitable patterns, enabling the development of profitable trading strategies, volatility forecasting, or option pricing (Hung et al., 2009). Guidi and Gupta (2011) investigated the weak-form efficiency of stock markets in the Association of Southeast Asian Nations (ASEAN) region and found that these markets do not exhibit a uniform trend. Their study suggests that the predictability of stock prices based on historical information varies across ASEAN countries, indicating a lack of consistent market efficiency within the region. Further, Kim and Shamsuddin (2015) provide a closer look into the dependence of return predictability in the US market using a panel variance ratio test, which shows that stock returns are highly predictable from 1964 to 1996 and unpredictable after 1997 to 2015. These findings align with the growing body of the literature. The notion of the adaptive market hypothesis (AMH) proposed by Lo (2004), which suggests that market efficiency is not a static condition but rather a dynamic state influenced by various factors, including market conditions, investor behaviour, and regulatory environments resulting in an alternative period of predictability (Urquhart & McGroarty, 2016). Dias and Peter (2020) conducted a non-parametric variance test to analysed integration and the time dependence of stock returns in sixteen countries over a period of 2002 to 2019. They provided evidence of mean reverting and time dependences of stock returns, and the random walk behaviour of stock returns failed to be rejected. However, the result is contradicted with the findings of Camba Jr and Camba (2020) in developing countries that the stock price movement is independent and identical to the past price movements.

The majority of the existing literature on market efficiency has primarily focused on investigating linear dependencies in stock markets, and the presence of nonlinear behaviour in international stock markets has been largely overlooked until the 1990s. The seminal work of Hinich and Patterson (1985) that estimates the bispectrum test is the first paper to investigate nonlinearity dependence in NYSE stock returns. The findings indicate that the daily returns of the 15 common stocks examined in the US stock market do not follow a linear process, but rather exhibit nonlinear dynamics and dependencies. This gap in research has prompted renewed interest in exploring the nonlinear dynamics within financial markets. Earlier studies have challenged the widely accepted random walk pattern by uncovering nonlinear behaviour in stock returns. Researchers such as Scheinkman and LeBaron (1989), Willey (1992), and Lima (1998) found evidence of nonlinearity in the US stock market. Similarly, Brock et al. (1991), Brooks (1996) and Opong et al. (1999) identified nonlinear patterns in the UK stock market, while Lim and Liew, (2006) and Lim et al. (2008) documented nonlinear behaviour in Asian stock markets, Alharbi (2009) in Gulf cooperation countries (GCC) and Krausz & Nam (2009) in the Pacific Badin stock market. Their findings contradicted the assumption of random walk and linear dynamics. Moreover, they suggested that markets are governed by nonlinear deterministic processes and are inherently unpredictable. Moreover, Lima (1998) documents that the October 1987 market crash has pivotal event catalysed widespread acknowledgement of the role of nonlinearities in the dynamics of stock returns. However, Brock et al. (1991) challenged the findings of nonlinearity in stock returns by attributing the observed patterns to the lack of stationarity in the return series. Abhyankar et al. (1995) found the presence of nonlinearity dependence on real time return on the FTSE 100 index using BDS test and Bispectrum (Hinich & Patterson,1985) test. In contrast to the findings suggesting nonlinear deterministic processes governing stock returns, Ahyankar et al. (1997) reported different results for real-time stock indices such as the S&P 500, DAX 30, Nikkei 225, and FTSE. Their study indicated that the behaviour of these stock indexes was primarily driven by a stochastic component, implying a significant independence in the price movements. This implies that the existence of alternating period characterised by linear and nonlinear dependencies. Consistent with the findings of Ahyankar et al. (1997), Ammermann and Pattersson (2003) investigated various global financial markets and Taiwan stock indices to assess the prevalence of nonlinear serial dependencies, suggesting that these nonlinear dependencies are not consistent over time. Instead, the data exhibited a pattern of brief episodes with extremely strong dependencies, followed by longer periods of relatively calm behaviour. Coupled with the transient and episodic disappearance of such dependencies was reported by Lim et al. (2013) for ASEAN countries, Lim et al. (2008) for ten emerging Asian markets and Bonilla et al. (2011) for Latin America.

The vast body of existing literature on nonlinear structures in stock returns across various economies has yielded contrasting results; Studies in emerging Asian capital markets (Sewell et al., 1993), G-7 countries (Sarantis, 2001), Tunisia (Saadi et al., 2006), South African stocks (Bonga-Bonga & Makakabule, 2010), Middle Eastern and North African (MENA) countries (Aimi et al., 2014) show evidence of non-linear dynamics in stock market returns and documented significant nonlinear dependencies between past stock prices and future price movements (Guhathakurta et al., 2016; Sammadder, 2021) in major stock indeices across emerging anf developed market. These findings imply that investors can earn abnormal profits by optimising their portfolios because of their predictable patterns or mean reversals. However, recent studies have presented contradictory evidence regarding nonlinear dependence in stock returns, particularly in Central and Eastern European (CEE) stock markets (Albulescu et al., 2021) and for major stock indices such as the Dow Jones Industrial Average, Ibex 35, Nasdaq-100, and Nikkei 225 (Inglada-Perez et al., 2020). Moreover, studies challenge the notion of widespread nonlinear dependencies, suggesting that the presence and extent of such dependencies may vary across different markets and time periods. Nusair and Olson (2022) demonstrate a differential long-run nonlinear stock return dependency on the G7 countries. Moreover, it can be noted the presence and existence of such dependencies may vary across different markets and time periods.

An episodic nonlinear dependency in the was found in Central and Eastern European (Todea & Zoicas-Ienciu, 2008), Asian Pacific market (Todea et al., 2009), US stock (Reboredo et al., 2012), Indian stock market (Hiremath & Kamaiah, 2010), developed market like S&P 500, FTSE 100, DAX, and Nikkei 225 (Demirer et al., 2019) and differences in long-run impact on G7 countries (Nusair & Olson, 2022).

3.2.1 Gap in the Empirical Studies

Numerous studies have investigated market efficiency using various approaches, including variance ratio tests. The findings are often inconsistent and vary across different markets, time periods, and market capitalisation levels. The choice of testing methodology (e.g., parametric or non-parametric variance ratio tests) may influence the conclusions regarding market efficiency, and a comprehensive approach combining multiple tests could provide more robust insights. Based on the literature, most studies have utilised the parametric and non-parametric VR tests. However, few existing literatures investigated the time dependence of the stock returns using parametric and non-parametric variance ratio tests with varying degrees of power and robustness. Despite the widespread application of these tests, a thorough comparative analysis of their relative testing approaches in capturing the time-dependent dynamics of stock returns across different market conditions remains unexplored.

The presence and extent of nonlinear dependencies in stock returns vary significantly across different markets and time periods, warranting a comprehensive comparative study to understand the underlying market dynamics and factors influencing these dependencies. The contradictory evidence regarding the presence of nonlinear dependencies in stock returns, particularly in certain developed markets such as the Central and Eastern European (CEE) stock markets and major indices like the Dow Jones Industrial Average, Ibex 35, Nasdaq-100, and Nikkei 225, necessitates further investigation to reconcile these findings and contribute to a more comprehensive understanding of market dynamics using a comparative analysis of developed and emerging financial markets. Based on the above discussion, the following hypotheses are formulated:

H_{1a}: The BRICS markets exhibit significant linear time-varying patterns.

H_{2a}: The BRICS markets exhibit significant nonlinear time-varying patterns.

H_{3a}: The G-5 markets exhibit significant linear time-varying patterns

H_{4a}: The BRICS markets exhibit significant nonlinear time-varying patterns.

H_{5a}: The degree of market efficiency changes over time differs in the G-5 and BRICS markets.

3.3. Data and Model Specification

3.3.1 Data

The study presents a comprehensive comparative analysis of market dynamics across two distinct economic blocs: the BRICS economies (Brazil, Russia, India, China, and South Africa) representing major emerging markets, and the G5 nations (United States, United Kingdom, France, Germany, and Japan) representing advanced economies. The analysis spans a 32-year period from 1990 to 2022, providing a robust longitudinal perspective that encompasses multiple economic cycles and global financial events. The study deliberately adopted 1990 as the starting point for analysis rather than utilising complete historical data from each index's inception. This methodological choice was motivated by several key considerations. Firstly, 1990 represented a significant milestone in global economic integration. This period witnessed reduced trade barriers, the adoption of market-oriented policies, an acceleration of financial globalisation, and market liberalisation policies across both developed and emerging economies (Bekaert & Harvey, 2017; Irwin, 2022). Secondly, this timeframe provides a consistent analytical window that encompasses critical global economic events, including the Asian Financial Crisis, dot-com bubble, 2008 Global Financial Crisis, and the COVID-19 pandemic, allowing for a comparative analysis of market behaviours during periods of systemic stress (Dungey et al., 2020).

Thirdly, robust time-series analysis in finance suggests that a 30 year timeframe provide sufficient data for robust analysis, allowing for the development and refinement of statistical models and inference techniques in time-series analysis (Chen et al., 2011; MacKinnon, 2013; Tong, 2011).

The sample period for the G5 market indices started from 1 January 1990 to 31 December 2022. The sample period for BRICS countries varied across stock market indices. The sample period for BSE is from 1 January 1990 to 31 December 2022; the SSE sample begins on 20 December 1990 to 31 December 2022; the IBOVESPA sample starts from 2 May 1990 to 31 December 2022; the JALSH sample begins on 30 June 1995 to 31 December 2022; and the MOEX sample begins from 22 June 1997 to 31 December 2022. The data availability constraints necessitated varied starting points for certain indices, particularly MOEX and JALSH which had shorter available data series[2]. The analysis employed data with varying temporal spans based on index inception and data availability constraints (Urquhart, 2013). This variation in index start dates aligns with established methodological approaches in cross-market research (Urquhart, 2013; Vo & Ellis, 2018). Utilising the maximum available data for each market while acknowledging temporal differences follows standard practices in multi-market studies (Majid & Kassim, 2009) and maintains analytical integrity despite different observation periods (Rizvi & Arshad, 2018). The data were obtained from two sources: The Trading Economics[3] Database and the official websites of the specific countries' stock exchanges under examination. The daily stock return for each of the countries' indices is computed as

$$r_{t,i} = \frac{\ln(p_{t)}}{\ln(p_{t-1})} \qquad (3.1)$$

Where $r_{t,i}$ is the return of the adjusted stock price/index at t, $\ln(p_t)$ is the natural log of index closing value/price of the index at period t, $\ln(p_{t-1})$ is the adjusted closing value/ price of index at period t-1. The returns calculated in this study

[2] The Johannesburg All Share Index (JALSH) data series was restricted to 1995-2022 as JSE upgraded to an electronic trading system and data availability only after this period (Marozva, 2020). The Moscow Exchange Index (MOEX) weightage capital index was launch in 1997 onward (Bagchi et al., 2020).
[3] https://tradingeconomics.com/stocks

do not account for dividends, because dividends are likely to be negligible and consistent in short-term predictions. Therefore, excluding dividends from the return calculations is unlikely to significantly impact the results, given the temporary nature of the analysis. The summary statistics which provide descriptive measures for the entire sample period as well as for sub-periods are presented in Table 3.1 for BRICS countries and Table 3.2 for G5 countries.

The descriptive statistics provided in Table 3.1 show the IBOVESPA has the highest mean return of 0.269, while the JALSH has the lowest daily average return of 0.038 in the overall sample. The standard deviation, a measure of the volatility of stock returns, shows that IBOVESPA is exceptionally high, while BSE shows lower volatility than the others. When subsamples are taken into consideration, The BSE average daily return decreases over time from 1990 to 2004, with a huge drop in the 2008-2013 subperiod and gradually increases afterwards. The SSE average daily shows negative return during 1993-1995, 2002-2004, 2008-2013 and 2017 – 2019. The IBOVESPA mean average return shows a gradual increase in mean return in the initial sample period and a negative return during 2011-13 and 2020-2022(possibly due to the global pandemic). The JALSH daily average return is negative during the Asian financial crisis (1996-1998) and shows the highest return during the period–2005-2007 subsample period. The MOEX mean daily return shows a negative return during the initial sample period, followed by a positive mean return and gradually drops during the 2000s this is during the period of recession and global pandemics. The standard deviation in the case of BSE was quite high during the 1990s and lasted until the 2000s during the bubble dot com and crash; the standard deviation gradually declined and increased during the global pandemic 2020-2022 sample period. The SSE Composite Index standard deviation showed a gradual increase during the 1990s and a decline until 2008-2010 and daily volatility showed a decline afterwards. The JALSH, IBOVESPA, and MOEX standard deviations show a high initially during 1990-1992 and later show a gradual decline until the 2008-2010 recession and the 2020-2022 global pandemic session. The subsample analysis in BRICS market shows that the mean return varies over time and the standard deviation constantly increases in major events such as the dot-com crisis, recession, and pandemics.

An analysis of skewness reveals the degree of symmetry of the return series. A positive skewness value indicates that the data are skewed to the right, whereas a negative value indicates that it is skewed towards the left tail. The return series for the BSE exhibits negative skewness in most sub-periods, except for 2008-2013 and 2017-2019. The SSE return series shows positive skewness in the initial period until 2004, followed by negative skewness in the subsequent sub-periods. The IBVESPA displays significant positive and negative skewness over different sub-periods. The JALSH sample period exhibits negative skewness in almost all sub-periods, except for 1993-1995 and 2002-2004.

Table 3.1: Descriptive statistics of daily return on BRICS countries.

	Obs	Mean	S.D.	Skewness	Kurtosis	JB	ADF	KPSS
Panel A: India (BSE Sensex)								
Full Sample	7979	0.054	1.605	-0.179	10.547	18967.21*	-16.50*	0.056
1990-1992	592	0.203	2.664	-0.091	6.538	309.69*	-5.49*	0.095
1993-1995	678	0.025	1.536	-0.004	4.525	65.73*	-17.92*	0.111
1996-1998	729	-0.003	1.695	-0.011	5.197	146.62*	-14.34*	0.035
1999-2001	748	0.008	1.925	-0.232	4.439	71.29*	-25.83*	0.059
2002-2004	759	0.092	1.314	-0.982	13.822	3825.86*	-12.45*	0.107
2005-2007	750	0.149	1.435	-0.378	5.551	221.25*	-19.89*	0.043
2008-2010	741	0.006	0.025	0.256	8.988	1115.28*	-9.26*	0.110
2011-2013	748	0.004	1.125	0.063	3.719	16.58*	-16.82*	0.034
2014-2016	746	0.030	0.919	-0.512	6.067	324.95*	-14.96*	0.073
2017-2019	739	0.059	0.748	0.404	6.741	451.02*	-16.09*	0.049
2020-2022	749	0.051	1.458	-1.610	20.430	9805.24*	-8.03*	0.114
Panel B: China (SSE Composite)								
Full Sample	7899	0.043	2.187	5.673	191.550	1174.15*	-13.70*	0.071
1990-1992	521	0.391	4.417	9.205	158.887	5348.71*	-23.50*	0.095
1993-1995	781	-0.041	3.702	1.540	15.986	5796.97*	-11.35*	0.061
1996-1998	784	0.093	2.104	-0.595	7.921	837.61*	-7.25*	0.021
1999-2001	718	0.053	1.509	0.501	8.795	1034.78*	-7.40*	0.047
2002-2004	721	-0.033	1.335	0.817	7.994	829.64*	-11.28*	0.046
2005-2007	725	0.199	1.706	-0.614	6.374	389.58*	-7.17*	0.128
2008-2010	732	-0.086	2.165	-0.139	4.972	120.95*	-27.11*	0.182
2011-2013	725	-0.041	1.136	-0.053	4.572	74.96*	-27.15*	0.032
2014-2016	733	0.052	1.775	-1.215	8.279	1031.71*	-6.60*	0.106
2017-2019	731	-0.004	1.025	-0.430	7.857	741.17*	-10.19*	0.079
2020-2022	728	0.002	1.123	-0.808	8.729	1075.02*	-26.44*	0.039
Panel C: Brazil (IBVOSPA or BVSP)								
Full Sample	7729	0.269	8.712	76.237	6379.19	111.31*	-47.64*	0.369
1990-1992	305	3.647	4.396	16.602	284.722	1022.64*	-17.86*	0.046
1993-1995	732	0.874	3.681	0.219	4.901	117.13*	-6.89*	0.146
1996-1998	737	0.059	2.842	-0.479	9.866	1475.98*	-7.46*	0.037
1999-2001	741	0.091	2.416	2.120	30.240	23465.01*	-26.40*	0.059
2002-2004	748	0.085	1.813	-0.278	3.631	22.05*	-26.39*	0.116
2005-2007	741	0.123	1.606	-0.296	3.640	23.48*	-20.31*	0.036
2008-2010	744	0.013	2.343	0.095	8.557	958.66*	-18.18*	0.111
2011-2013	743	-0.041	1.409	-0.246	5.104	144.57*	-27.36*	0.039
2014-2016	754	0.024	1.565	0.171	3.707	19.39*	-27.56*	0.053
2017-2019	738	0.089	1.249	-0.644	7.426	653.40*	-10.74*	0.036
2020-2022	746	-0.010	1.972	-1.457	19.760	8995.72*	-7.86*	0.071
Panel D: South Africa (JALSH)								
Full Sample	7018	0.038	1.207	-0.515	9.799	1382.05*	-32.11*	0.032
1993-1995	227	0.108	0.526	0.294	3.001	1.84	-10.23*	0.023
1996-1998	753	-0.015	1.356	-1.607	17.759	7158.81*	-13.92*	0.045
1999-2001	746	0.098	1.248	-0.279	7.183	553.48*	-23.84*	0.072
2002-2004	751	0.025	1.077	0.104	3.555	11.01*	-17.35*	0.067
2005-2007	749	0.111	1.163	-0.536	6.087	333.40*	-27.89*	0.039
2008-2010	773	0.013	1.685	-0.033	5.362	179.87*	-15.54*	0.065
2011-2013	782	0.046	0.938	-0.257	4.327	66.05*	-21.19*	0.031
2014-2016	783	0.012	0.965	-0.166	4.379	65.55*	-21.53*	0.023
2017-2019	778	0.015	0.845	-0.115	4.478	72.60*	-28.02*	0.038
2020-2022	776	0.032	1.4281	-0.804	10.718	2010.02*	-7.36*	0.051
Panel E: Russia (MOEX)								
Full Sample	6320	0.049	2.463	-0.567	31.307	211347.1*	-13.01*	0.037
1996-1998	319	-0.248	5.893	0.332	7.076	226.75*	-15.40*	0.083
1999-2001	750	0.221	2.992	0.197	4.977	127.04*	-23.41*	0.101
2002-2004	748	0.113	1.931	-0.475	5.736	261.48*	-15.77*	0.048
2005-2007	744	0.165	1.861	-0.604	7.286	614.83*	-29.24*	0.033
2008-2010	747	-0.015	3.243	0.045	15.149	4594.52*	-7.052*	0.111
2011-2013	753	-0.013	1.356	-0.643	6.002	334.76*	-26.42*	0.024
2014-2016	759	0.052	1.261	-0.898	12.421	2909.01*	-27.40*	0.027
2017-2019	760	0.041	0.889	-1.068	15.416	5026.92*	-27.56*	0.049

2020-2022	740	-0.047	2.358	-6.584	124.625	461457.7*	-31.03*	0.076

Source: *Author's computation Using EViews*

Note(s): This table represents descriptive statistics of the full sample and subsample among BRICS countries. The JB test is the Jarque- Bera test for goodness-of fit test to examine whether the sample return is in normal distribution. Two stationarity tests Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test suggest return are stationary. *, **, *** denotes a significant at 1%, 5% and 10% respectively.

The MOEX sample shows negative skewness during 1996-1999 and 2000-2001, and positive right-tail skewness in the subsequent periods. The Kurtosis in all five indices exceeds 3, which implies a leptokurtic distribution. IBOVESPA had the highest leptokurtic distribution, and JALSH had the smallest. The deviation of skewness and kurtosis values for these five indices indicates that the distribution of their return series deviates from normality and indicating the indices return series are not normal. Further, the extent of non-normality investigation was conducted using the Jarque-Bera (JB) test, a goodness-of-fit test for normality, which indicating that the daily distribution of returns deviates significantly from the normal distribution, as evidenced by the non-zero values. This finding suggests that the return series of the BRICS indices are not normally distributed.

The descriptive statistics provided in Table 3.2 show that DAX 30 has the highest mean return of 0.045, while the Nikkei 225 has the lowest daily average return of -0.002 in the overall sample. The standard deviation, a measure of the volatility of stock returns, shows that DAX is relatively high, while FTSE 100 shows lower volatility than the others. When subsamples are considered, The CAC 40 and DAX 30 average daily returns show a negative return during 1990-1992, 2002-2004, and 2008-2010 and otherwise, positive mean returns are exhibited. The FTSE 100 mean average return shows a gradual increase in mean return in the initial sample period and shows a negative return during the 2000s and 2020-2022, possibly due to dot com bubbles, recession, and the global pandemic. The Nikkei daily average return show a negative during the 1990s and the global financial crisis (2008-2010) and showed a positive return afterwards. The S&P 500 mean daily return shows a positive return in almost all periods, except for the sub-period–1999-2001 and 2008-2010. The standard deviation for the CAC 40 sub-period is quite high during the global financial crisis and global pandemic, and shows the least volatility during the 2017-2019 sub-period. The DAX 30 standard deviation shows a gradual decrease during the 1990s, a gradual increase in the 2000s, and a similar trend to the CAC 40 movement. The FTSE 100, Nikkei 225, and S&P 500 standard deviations were the highest during the sample period in 2008-2010 and show a gradual decline during till 2017-2019 and later increased during the global pandemic. The subperiod analysis in G5 countries show mean return varies overtime and the standard deviation constantly increases in major events like dot com crises, recessions, and pandemics. An analysis of skewness reveals that CAC 40 exhibits negative skewness in most sub-periods, except for 1993-1995, 2002-2004, and 2008-2013. The DAX 30 return series show a negative skewed for all the sample period except 2002-2004 and 2008-2013 sample period. The FTSE 100 displays significant negative skewness over different sub-periods except for 1990-1992. The Nikkei 225 return series shows positive skewness in the initial period until 1998, followed by negative skewness in the subsequent sub-periods. The S&P 500 shows a negative skew in the sample period 2002-2004 and other periods exhibit a left tail toward the normal distribution. The Kurtosis in all five indices exceeds 3, which implies that a leptokurtic distribution and the period 2020-2022 show the highest kurtosis in all indices. S&P 500 had the highest leptokurtic distribution, and DAX 30 had the smallest. The deviation of skewness and kurtosis values for these five indices indicates that the distribution of their return series deviates from normality and indicating the indices return series are not normal. Further, the extent of non-normality investigation was conducted using the Jarque-Bera (JB) test, a goodness-of-fit test for normality, indicates that the daily distribution of returns deviates significantly from the normal distribution, as evidenced by the non-zero values. This suggests that the returns series of G5 indices are not normally distributed.

Table 3.2. Descriptive statistics of daily return on G5 countries.

	Obs	Mean	S.D.	Skewness	Kurtosis	JB	ADF	KPSS
Panel A: France (CAC 40)								
Full Sample	8387	0.014	1.367	-0.187	8.739	11556.69*	-92.13*	0.050
1990-1992	751	-0.010	1.253	-0.167	6.854	468.31*	-26.25*	0.052
1993-1995	749	0.002	1.064	0.060	3.004	0.45	-27.10*	0.048
1996-1998	748	0.097	1.329	-0.250	5.464	196.94*	-25.71*	0.050
1999-2001	760	0.017	1.447	-0.269	4.163	52.05*	-27.03*	0.066
2002-2004	769	-0.024	1.658	0.100	5.504	202.15*	-28.16*	0.087
2005-2007	767	0.050	0.909	-0.385	4.152	61.31*	-29.47*	0.027
2008-2010	770	-0.051	1.952	0.233	8.097	840.62*	-29.97*	0.074
2011-2013	768	0.014	1.408	-0.146	5.343	178.40*	-27.27*	0.042
2014-2016	768	0.016	1.263	-0.516	6.375	398.71*	-27.59*	0.052
2017-2019	765	0.027	0.795	-0.270	5.346	184.66*	-26.69*	0.062
2020-2022	772	0.010	1.524	-0.966	14.183	4142.63*	-28.12*	0.096
Panel B: Germany (DAX 30)								
Full Sample	8360	0.045	1.407	-0.188	8.6739	11263.65*	-15.66*	0.039
1990-1992	746	-0.002	0.013	-0.348	10.001	1538.99*	-15.29*	0.061
1993-1995	755	0.051	0.933	-0.093	3.560	**12.39****	-27.33*	0.070
1996-1998	751	0.105	1.444	-0.454	6.302	366.92*	-5.22*	0.070
1999-2001	760	0.004	1.601	-0.209	4.814	109.69*	-27.49*	0.056
2002-2004	763	-0.025	1.936	0.082	4.708	93.63*	-9.45*	0.092
2005-2007	764	0.083	0.907	-0.374	3.770	36.65*	-28.44*	0.035
2008-2010	770	-0.020	1.836	0.269	8.785	1082.99*	-13.79*	0.048
2011-2013	770	0.042	1.353	-0.261	5.688	240.44*	-14.14*	0.036
2014-2016	760	0.024	1.296	-0.369	4.688	107.50*	-13.59*	0.056
2017-2019	755	0.018	0.855	-0.269	4.4666	76.79*	-14.34*	0.088
2020-2022	766	0.007	1.563	-0.639	13.9459	3876.22*	-9.49*	0.061
Panel C: United Kingdom (FTSE 100)								
Full Sample	8413	0.001	0.011	-0.274	10.859	21756.93*	-43.08*	0.035
1990-1992	784	0.026	0.906	0.457	6.144	350.29*	-26.84*	0.065
1993-1995	781	0.033	0.696	-0.127	3.331	5.655	-26.75*	0.065
1996-1998	771	0.061	1.011	-0.311	6.529	412.60*	-20.41*	0.056
1999-2001	752	-0.016	1.195	0.025	3.637	12.79*	-21.51*	0.018
2002-2004	749	-0.011	1.269	-0.096	6.735	436.73*	-29.16*	0.064
2005-2007	742	0.040	0.849	-0.464	6.407	385.40*	-30.14*	0.022
2008-2010	775	-0.012	1.705	-0.038	8.663	1036.06*	-13.47*	0.063
2011-2013	782	0.017	1.008	-0.264	5.350	189.13*	-27.09*	0.099
2014-2016	760	0.007	0.969	-0.146	5.067	138.06*	-14.52*	0.032
2017-2019	759	0.008	0.702	-0.399	5.001	146.77*	-17.31*	0.071
2020-2022	759	-0.002	1.313	-1.101	15.636	5203.02*	-13.04*	0.035
Panel D: Japan (Nikkei 225)								
Full Sample	8226	-0.002	0.015	-0.140	8.469	10281.50*	-93.24*	0.028
1990-1992	739	-0.113	1.784	0.541	7.144	564.95*	-21.25*	0.0476
1993-1995	742	0.021	1.285	0.314	6.525	396.39*	-27.34*	0.118
1996-1998	740	-0.048	1.523	0.141	5.339	171.23*	-22.98*	0.034
1999-2001	739	-0.036	1.543	-0.027	4.923	113.97*	-28.82*	0.067
2002-2004	737	0.011	1.420	-0.128	3.559	11.613*	-26.90*	0.063
2005-2007	738	0.038	1.107	-0.362	4.550	89.997*	-27.30*	0.064
2008-2010	733	-0.055	2.115	-0.339	9.002	1114.14*	-28.73*	0.067
2011-2013	741	0.062	1.435	-1.028	9.905	1602.81*	-28.50*	0.039
2014-2016	749	0.021	1.438	-0.161	7.435	617.20*	-29.40*	0.092
2017-2019	837	0.025	0.949	-0.602	6.712	531.09*	-31.34*	0.059
2020-2022	837	0.040	0.036	-6.27	6.321	413.51*	-16.96*	0.074
Panel E: U.S (S&P 500)								
Full Sample	8343	0.028	1.153	-0.396	13.63	3955.58*	-99.04*	0.072
1990-1992	758	0.025	0.854	-0.027	4.643	85.33*	-25.86*	0.063
1993-1995	757	0.046	0.555	-0.255	4.764	106.42*	-27.01*	0.112
1996-1998	755	0.092	1.079	-0.674	9.426	1356.47*	-27.48*	0.036
1999-2001	752	-0.009	1.304	-0.007	4.238	48.06**	-27.10*	0.032
2002-2004	756	0.007	1.201	0.253	4.993	133.19*	-28.86*	0.077

2005-2007	754	0.025	0.782	-0.352	5.156	161.74*	-30.85*	0.059
2008-2010	757	-0.020	1.910	-0.164	8.719	1035.12*	-23.45*	0.072
2011-2013	755	0.051	1.053	-0.583	8.259	913.01*	-14.85*	0.028
2014-2016	757	0.025	0.845	-0.351	5.257	176.16*	-27.58*	0.039
2017-2019	756	0.048	0.807	-0.705	8.438	994.35*	-28.43*	0.048
2020-2022	786	0.022	1.581	-0.754	14.398	4329.96*	-8.19*	0.061

Source: *Author's computation Using EViews*

Note(s): This table represents descriptive statistics of full sample and subsample among G5 countries. The JB test is Jarque- Bera test for goodness-of fit test to examine whether the sample return is in normal distribution. Two stationarity test Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test suggest return are stationary. *, **, *** denotes a significant at 1%, 5% and 10% respectively.

3.3.2. Linearity Methodology

The linearity tests are conducted using the autocorrelation test, the variance ratio test and joint variance ratio test.

3.3.2.1 Autocorrelation test

Autocorrelation is a statistical tool used to measure the correlation between a time series and its own lagged values. It is an important tool for analysing time series data and identifying patterns or dependencies within the data. The autocorrelation test is used to determine whether there is significant autocorrelation present in a time series by a specific lag. If auto-correlation are found, returns are not independent, which implies that returns are not linear autocorrelation dependences in the series. Autocorrelation occurred when the covariance and correlation between different disturbances are not all non-zero. The autocorrelation function is given by:

$$\rho_k = \frac{\gamma_k}{\gamma_0} \tag{3.2}$$

$$\gamma_k = \frac{\sum(X - \bar{x})(X_{t+K} - \bar{x})}{n} \tag{3.3}$$

$$\gamma_0 = \frac{\sum(X - \bar{x})^2}{n} \tag{3.4}$$

Where, ρ_k is the autocorrelation function at lag k, γ_k is the covariance at lag k and γ_0 is the variance. n is the sample size and $\bar{x}$ is the mean value. The order of an autoregressive process specifies the number of lagged (past) values that influence the current value. In a first-order autoregressive process containing lagged value of one (ϵ_t) the current value is influenced by the immediately preceding period (ϵ_{t-1}). In same way, a second order process containing lagged value of two (ϵ_t) the current value is influenced by the immediately preceding two period, i.e., $\epsilon_{t-1}, \epsilon_{t-2}$.

There are three cases of autocorrelation concerning the parameter ρ:

1. **Positive Autocorrelation**: If the parameter $\rho > 0$, it indicates positive autocorrelation. This means that the current value is positively influenced by its past values, and a negative value of ϵ_{t-1} tend to followed by a negative value of ϵ_t. A positive ρ implies that previous value random disturbance results to spill over effect to the next period.
2. **Negative Autocorrelation**: If the parameter $\rho < 0$, it indicates negative autocorrelation. This means that the current value is negatively influenced by its past values, also known as a contrarian effect, and a negative value of ϵ_{t-1} tend to followed by a positive value of ϵ_t.
3. **No Autocorrelation**: If the parameter ρ of the autoregressive process are equal to zero, it indicates no autocorrelation. This means that ϵ_t is not influenced by ϵ_{t-1} and implies that the current value is independent of the previous value.

The autocorrelation test assesses whether the correlation coefficients significantly differ from zero. The null hypothesis is that the current price movement is not influencing the previous stock price value ($\rho = 0$). This would imply a random walk process. Under the null hypothesis of no autocorrelation, the t-statistic is outside a $[\pm 2.58/\sqrt{\mathrm{T}}]$, $[\pm 1.96/\sqrt{\mathrm{T}}]$, or $[\pm 1.64/\sqrt{\mathrm{T}}]$ band for 1%, 5% and 10% significance respectively. Where T represents the total number of observations or data points in the sample. Market efficiency implies asset returns should be independent over time, necessitating examination of the autocorrelation function up to the maximum feasible lag to confirm no significant autocorrelations in the return series. This study focuses on the first order autocorrelation even up to 20 lags are reported.

3.3.2.2 Variance Ratio Test

The variance ratio test is one of the most widely used statistical techniques for investigating whether time series stock returns exhibit serial correlation or not. It is among the most commonly employed econometric tools for testing the random walk hypothesis (Hoque et al., 2007; Zhou & Lee, 2013). The variance test is an increments subject to a number of developments in recent year (Charles & Darne, 2009).

The variance ratio test (VR), introduced by Lo and MacKinlay (1988), is a fundamental test for detecting serial correlation in stock return series. The VR test is premised on the notion that for a series to follow a random walk, the variance of the k-period return should be equal to k times the variance of the one-period return. Consequently, if a time series follows a random walk, the variance of 10-period differences should be 10 times the variance of its daily return. Lo and MacKinlay (1988) developed a test to examine the random walk hypothesis using a single variance ratio, denoted by $(VR(k)$. The test statistic can be expressed as follows:

$$VR(k) = {}^{\sigma_k^2}\!/_{k\sigma^2} \tag{3.5}$$

Where, σ_k^2 is the variance variance of K period return ($\sigma_k^2 = Variance\ (r_t + r_{t-1} + \cdots . + r_{t-k+1})$. The expression can be rewritten as:

$$VR(k) = 1 + 2\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)\rho(j) \tag{3.6}$$

Where $\rho(j)$ is the j[th] order autocorrelation coefficient of r_t. This shows that VR(K) is a particular linear combination of the first *k-1* autocorrelation coefficient of r_t, with linearly declining weights. The null hypothesis: VR test = 1 ∀ k, return is serially uncorrelated with $\rho(j) = 0$. When VR>1, imply positive and serial correlated and VR<1 implies negative serial correlation or mean reversal.

There is a question regarding the asymptotic variance of the variance ratio test statistic. Lo and MacKinley (1988) proposed that under very general conditions it is possible to write:

$$\overline{VR}(k) = 1 + 2\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)\hat{\rho}(j) \tag{3.7}$$

The asymptotic variance $\hat{\theta}(q)$ of $\overline{VR}(k)$ can be calculated as the weighted sum of δ_k, which are the asymptotic variances of autocorrelations $\hat{\rho}(j)$. Lo and MacKinley (1988) showed that the following heteroskedasticity consistent estimator of δ_k:

$$\hat{\theta}(k) = \sum_{k=1}^{q-1}\left(\frac{2(q-k)}{k}\right)^2 \hat{\delta}(k) \tag{3.8}$$

$$\hat{\delta}(k) = \frac{nq\ \sum_{j=k+1}^{nq}(p_j - p_{j-1} - \hat{\mu})^2 (p_{j-k} - p_{j-k-1} - \widehat{\mu})^2}{\left[\sum_{j=1}^{np}(p_j - p_{j-1} - \hat{\mu})^2\right]} \tag{3.9}$$

Testing of the null hypothesis H_0^* can be expressed as in Equation 3.10:

$$\hat{\theta}^*(k) = \frac{\sqrt{nq}\,\overline{VR}(k)}{\sqrt{\hat{\theta}(k)}} \sim a\ \mathrm{N}(0,1) \qquad (3.10)$$

The study employed $\hat{\theta}(k)$ a heteroscedasticity-robust test statistic. Due to the presence of heteroscedasticity in the return series, as evidenced by the results presented in Table 3.1 and Table 3.2. When computing the variance ratio $VR(k)$, the holding period k must be specified. While there is no definitive guideline, the literature commonly employs values of 2, 4, 8, and 16 for daily return data. Despite being somewhat arbitrary choices with limited theoretical justification, these values have become standard practice in many studies (Choi, 1999, Urquhart, 2013).

3.3.2.3. Chow and Denning (CD) Test

According to the random walk hypothesis, the variance ratio for all holding periods should be equal to unity, and the test should be done concurrently over many holding periods. (Charles & Darné, 2009; Hiremath & Kumari, 2014). To overcome the problem, Chow and Denning (1993) test offered a multivariance ratio test to assess whether the number of distinct holding periods is jointly equal to one in order. Furthermore, the multivariate ratio is more powerful than the test against ARIMA (1,1,1) and ARIMA (1,1,0) and extends the conventional variance ratio test methodology proposed by Lo and MacKinlay (1988). Their approach involved formulating a multiple variance ratio test that leveraged the Lo-MacKinlay (1998) test statistics as studentized maximum modulus (SMM) statistics.

In the Lo-McKinley test, the null VR(q) = 1, but in multiple variance ratio test, M_r= (q_i) = VR(q) -1 = 0 which is generalised to set of m variance ratio test as

$$\{M_r(q_i)|\ i = 1,2, \dots \dots, m\} \qquad (3.11)$$

Under the random walk null hypothesis there are multiple sub-hypotheses.

H_{01}: $M_r(q_i) \neq 0$ for any $i = 1,2, \dots \dots, m$

Rejection in H_0 means rejection of random walk null hypothesis. The heteroscedasticity of Chow and Denning statistic in equation (3.12)

$$CD = \sqrt{T}\ Max\ |Z^*(q_1)| \tag{3.12}$$

Where, $Z^*(q_1)$ is heteroskedasticity robust test statistics. Studentized Maximum Modulus, SMM ($\alpha,\ m\ , T$), distribution with m parameter and T degrees of freedom is used in the Chow-Denning test. If the value of the standardised test statistic CD is more than the SMM critical significant value, the random walk is rejected.

3.3.2.4 Wright Rank and Sign Test

Further, a non-parametric variance ratio test was employed to the variance ratio test. The Rank and sign proposed by Wright (2000) is a non-parametric solution to the conventional VR test that addressing potential issues arising from biased and right-skewed samples. The tests have a higher power against a model demonstrating serial correction, are more effective than the Lo-MacKinlay (1988) VR test. The signs-based test exhibits robustness against a wide range of models exhibiting serial correlation, even in the presence of conditional heteroscedasticity. Furthermore, the ranks-based test exhibits minimal size distortion when heteroscedasticity is present (Belaire-Franch & Contreras, 2004). Wright's proposed R1 and R2 in equation 6 and equation 7 are defined as follows for T observations of first differences of a variable stock price {y_1,..., y_T}. The test statistic based on ranks test is given in Equation (3.15).

$$R_j(k) = \left(\frac{\frac{1}{Tk}\sum_{t=K}^{T}\left(r_{jt} + \ldots + r_{jt-k+1}\right)^2}{\frac{1}{t}\sum_{t=1}^{T} r_{jt}^2} - 1\right)\left(\frac{2(2k-1)(k-1}{3kT}\right)^{-1/2} \tag{3.15}$$

Where,

$$R_{1t} = \frac{\left[r(rt) - \left(T + \frac{1}{2}\right)\right]}{\sqrt{(T-1)(T+1)/12}} \tag{3.16}$$

$$R_{2t} = \frac{\varphi^{-1} r(r_t)}{T+1} \tag{3.17}$$

Where, φ^{-1} is the inverse of the standard normal cumulative distribution function.

The tests based on the sign test for the observation is given in eq.(8):

$$S_j(k) = \left(\frac{(TK)^{-1}\sum_{t=K}^{T}\left(S + \ldots + S_{jt-k+1}\right)^2}{T^{-1}\sum_{t=1}^{T} S_{jt}^2} - 1\right)\left(\frac{2(2k-1)(k-1}{3kT}\right)^{-1/2} \tag{3.18}$$

Where, $s_t = 2u(y_t, 0)$ and $u(y_t, 0)$ is $1/2$ if y_t is positive and -1/2 otherwise. Under the assumption that r_t is a no-drift martingale difference sequence, s_t is an i.i.d.

sequence with zero mean and unit variance, and the critical values can be calculated by simulating its sampling distribution as listed in Wright (2000).

3.3.3. Nonlinear Methodology

A nonlinear test is used to detect and quantify the presence of nonlinear patterns or dynamics in the data. These tests are particularly important because many real-world time series exhibit nonlinear behaviour, which cannot be adequately modelled using traditional linear methods. Nonlinear tests help researchers identify when nonlinear modelling approaches are necessary to capture the underlying dynamics of the time series accurately. One commonly used nonlinear test in time series analysis is the BDS test, proposed by Brock, Dechert, and Scheinkman (1996). The BDS test is a Portmanteau test that can detect a broad range of deviations from linearity, including chaos, nonlinear stochastic processes, and non-Gaussian. The test statistic is based on the correlation integral, which measures the probability that pairs of points in the time series are within a certain distance of each other.

Instead of using a single statistical test, a battery of nonlinear tests are employed to examine the nonlinear structure in stock returns, enabling a more comprehensive and in-depth analysis of the data, minimising the likelihood of overlooking crucial patterns and drawing inaccurate conclusions. By employing a battery of nonlinear tests, researchers can cross-validate their findings and establish a consensus regarding the presence and nature of nonlinearities in the stock return series. If multiple tests unanimously point towards a specific result, this outcome can be deemed more reliable and accurate.

The linear underpinnings inherent in the return series are effectively eradicated through the deployment of a pre-whitening model. The pre-whitening of data is a pivotal step in the analysis and modelling of nonlinear time series. The primary objective of this procedure is to remove any linear dependence structures present in the data, thereby isolating the nonlinear component and ensuring that the residuals exhibit independent and identically distributed (i.i.d.) noise characteristics. Utilising the Ljung-Box Q-statistic, an AR (ρ) model is fitted to the data yielding residuals that devoid any remaining linear dependencies for the presence of residual autocorrelation.

Computed up to 20 lags thereby indicating that the linear dependence structure has been adequately captured by the AR (ρ) model (Hsieh, 1989, Urquhart, 2013). The Q-statistic is computed up to 20 lags, and if the resulting value is not statistically significant at the 10% significance level this condition implies that the chosen AR model adequately accounts for the nonlinear dependencies in the data and will be chosen for nonlinearity test. Specifically, it tests the null hypothesis that all autocorrelations are zero, implying that the series is white noise (Box & Pierce, 1970).

The Ljung-Box Q-statistic for serial correlation is given by:

$$Q_{LB} = T(T+2)\sum_{j=1}^{n} \frac{\rho_j^2}{(T-j)} \tag{3.19}$$

Where ρ_j is the estimated autocorrelation on a given time series and T is the number of observations. Show that as T for a larger sample, the Ljung-Box tend toward a Chi-square distribution with n degree of freedom. The study reports the computed Q-statistics in Appendix-I (Table 1 and Table 2). These results align with the previously observed patterns in the autocorrelation functions. The authors plan to subject the residuals from the pre-whitening model to a comprehensive suite of nonlinear tests including the McLeod and Li test (1983), the Engle LM test (1982), and the BDS test (1996). These tests are designed to detect any remaining nonlinear dependencies that may be present in the residuals, even after accounting for linear dependencies through the whitening model.

3.3.3.2. McLeod Li Test

The McLeod-Li (1983) test is a statistical test used to detect the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the residuals of a time series model. It is a portmanteau test that checks for nonlinear dependencies in the squared residuals. The proposed test statistic for the McLeod-Li test (1983) is defined as:

$$Q(m) = \frac{n(n+2)}{n-k}\sum_{k=1}^{m} r_a^2(k) \tag{3.20}$$

$$r_a^2(k) = \frac{\sum_{t=k+1}^{n} e_t^2 e_{t-k}^2}{\sum_{t=k}^{n} e_t^2} k = 0,1, \dots \dots, n-1$$

(3.21)

Where $r_a^2(k)$ is square residual autocorrelation at lag k, n is a sample size, e_t^2obtained from fitting a model to the data. The null hypothesis being tested is that the returns or residuals are independent and identical distribution, implying the absence of any serial correlation or dependence structure. If the null hypothesis is rejected, it suggests the presence of autoregressive conditional heteroskedasticity (ARCH) or generalized ARCH/GARCH effects in the data, indicating the existence of nonlinear dependencies.

3.3.3.3. Engle LM test

The Engle (1982), a Lagrange Multiplier (LM) test is utilised to detect the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the residuals of a time series model. It is similar in spirit to the McLeod-Li test but uses a different approach. The residual of AR (ρ) model are tested for heteroscedasticity. The Engle LM test is based on the auxiliary regression and computed as:

$$e_t^2 = \alpha_0 + \sum_{i=1}^{p} a_i e_{t-1}^2 + v_t \tag{3.22}$$

Where e_t^2 is the residuals from the original time series model from the whitened AR (ρ) model, v_t is the error term. The test statistic utilised F-statistic for the regression on the squared residual are computed as:

$$F_{Statistic} = \frac{RS-UR}{UR} \times \frac{T-k}{m}$$

(3.23)

Where RS represents the residual sum of squares obtained from fitting a restricted regression model, UR represents the residual sum of squares obtained from fitting an unrestricted regression model, m denotes the number of restrictions or constraints imposed on the restricted regression model compared to the unrestricted model. T is the total number of observations and k is the number of predictor variables or regressors included in the unrestricted regression model. Under the null hypothesis, LM statistic exceeds the critical value from the chi-squared distribution at the chosen significance level, the null hypothesis of no ARCH effects is rejected, indicating the presence of conditional heteroskedasticity or time-varying volatility in the residuals.

3.3.3.4 BDS Test

The Brock-Dechert-Scheinkman (1987) or BDS test was initially designed for time-based dependent series and frequently used non-parametric test for serial dependence in time series (Chen & Yeh, 2002). The BDS test is the most powerful nonlinearity test because it does not require adjustment to a correction when applied to residuals nor it necessitate the existence of higher moments (Brito-Cervantes et al., 2018; Chen & Yeh, 2002; Patterson & Ashkey, 2000). This flexibility enhances the robustness of the BDS test, making it well-suited for analysing financial data, which often deviates from normality assumptions. AR-GARCH (1,1) was fitted to the return based on the Akaike information criterion (AIC) and the standardised residuals are then checked for independent and identically distributed variance using the BDS test. The BDS test model is computed in the following:

Let $\{u_t\}$ be the stochastic process with value of embedded dimension m is determined in the flowing process as:

$u_t^m = (u_t, u_{t+1} \dots \dots \dots \dots, u_{t+m-1})$

The correlation integral at the embedded dimension, m, for $\in > 0$, is estimated by the following equation. (3.24):

$$C_{m,\in} = \left(\frac{1}{\frac{T}{2}}\right) \sum_{1<s<t<T} \sum I_{\in}(u_t^m, u_s^m) \quad (3.24)$$

Where $\underline{T} = T - (M-1), I_{\in}(\dots)$ is the symmetric indicator kernel. $I_{\in}(z, \omega = 1)$, other zero.

If $\{u_t\}$ is an i.i.d. process with a non-degenerate cumulative distribution F, then for fixed $\in > 0$ and m=1,2….. $C_{m,e} \rightarrow C(\in)^m, T \rightarrow \infty$, with a probability of one, where

$$C(\in) = \int \{F(Z + \in) - F(Z - \in)\} dF(Z) \quad (3.25)$$

Brock, Dechert and Scheinman (1987) defined the BDS statistic in equation (3.26):

$$V_{m,\in} = \sqrt{T} \frac{C_{m,e} - C(\in)^m}{S_{m,\in}} \quad (3.26)$$

Where, T is the sample size, $\in$ id the arbitrage chosen proximity parameter, $S_{m,e}$ is a constant estimator of the asymptotic standard deviation. The null hypothesis

$\{u_t\}$ is i.i.d, $V_{m,\in}$ ~ N(0,1) $\forall \in > 0,$ and m=2,3,4……, n. The rejection of the null hypothesis invalidates the notion of market efficiency, as the test serves as a measure of nonlinear predictability in the sample data.

The BDS statistic $V_{m,\in}$, has asymptotically followed a normal distribution when the data series comprises more than five hundred observations (Brock et al., 1991). Hsieh (1991) noted that structural changes in the data series could lead to a rejection of the null hypothesis of independent and identically distributed (i.i.d.) observations based on the BDS test results. Consequently, it is advisable to split the data into subsamples and analyse them separately. A critical aspect of the BDS test is the choice of the parameter '∈,' which represents the maximum distance between pairs. A larger value of '∈' retains all pairs, resulting in a correlation integral value of unity, while a smaller value may exclude all pairs, leading to a zero-correlation integral value. The ∈ used are 0.5σ, 1σ, 1.5σ and 2σ, which are similar to majority of the earlier literature (Brook et al; 1991, Sewell, et al., 1993, Urquhart, 2013). The choice of the embedded dimension was based on (Hsieh, 1989) suggestion i.e., a broad range values from 2 to 10 for the parameter.

3.4. Empirical Results for linearity test

3.4.1. Autocorrelation test result for BRICS markets

This section discussed the result for the linearity test explained in the above section. Table 3.3 and Table 3.4 report the autocorrelation coefficient for the BRICS countries and G5 countries respectively. The full sample in Table 3.3 possesses a significant first order in BSE and SSE and shows a significant positive and negative at other order autocorrelation at lag 5, lag 10 and Lag 20 were found, this indicates that stocks are predictable on the past price movement. The result of the autocorrelation test in Table 3.3 also documents the coefficient of the subsample for BRICS countries. In BSE, the result shows a first order autocorrelation for the sample period 1993-1995 and 2002-2004 show a negative significance, suggesting a mean-reverting pattern or a tendency for the series to oscillate around its mean. A significant positive first order autocorrelation during the sample 2017-20019 and 2020-2022, suggesting persistence or a continuation of the trend. The initial subsample period 1990-1998 show a significant autocorrelation on various lags under consideration. However, the sample period 1990-2001 show no significant autocorrelation in any of the lags. The period 2002-2004 show a significant autocorrelation in all the lag and no significant the autocorrelation was found during the period of 2005-2016 over 4 different subsamples. This indicate that the stock return was independent during this period. The subsample for the 2017-19 show a significant autocorrelation on lags 1, lag 10 and lag 15 and 2020-2022 show a significant autocorrelation in any of the lags. The result of the BSE suggest that the return undergoes through a period of independent and through a period of dependent. Thus, the behaviour of return appears to follow the AMH and can be categorised by type 4 and the null hypothesis H_{01a} is rejected.

Panel B of Table 3.3 show the autocorrelation result of SSE composite Index. The subsamples reveal distinct behaviours. The periods 1999-2001 and 2005-2007 exhibit negative first-order autocorrelation, implying a mean-reverting pattern where the series oscillates around its mean. The initial subsample from 1990-2000 shows significant autocorrelation at various lags under consideration. Interestingly, the 2002-2004 subsample displays no significant autocorrelation at any lag, indicating independence of stock returns during this period. The 2005-2007 subsample exhibits significant autocorrelation at all lags, while no significant autocorrelation is found during the 2008-2010 and 2011-2013 subsamples, suggesting independence of stock returns. The subsamples in 2014-2016 and 2017-2019 exhibit significant autocorrelation at lags 5, 10, 15, and 20, indicating potential predictability. However, the 2020-2022 subsample shows no significant autocorrelation at any lag, implying independence of stock returns during this period. The behaviour of returns appears to follow the AMH and can be categorised as Type 4, where the market alternates between periods of efficiency and inefficiency. Thus, the null hypothesis H_{01a} is rejected, which implies returns exhibiting varying degrees of predictability and independence over time.

Panel C of Table 3.3 documented the autocorrelation coefficient of IBOVESP. The full sample does not exhibit significant first-order autocorrelation, it shows substantial autocorrelation at lags 5, 10, 15, and 20, suggesting potential predictability based on past price movements. Considering the subsample period, the initial subsample period from 1990-1992 does not display significant autocorrelation at any lag, indicating independence of stock returns during this time. However, the 1996-1998 subsample exhibits significant autocorrelation at various lags, suggesting predictability. The subsamples for 1993-1995 and 1999-2001 show significant autocorrelation at various lags, while no significant autocorrelation is observed during the 2002-2004 and 2005-2007 subsamples, implying independence of stock returns during these periods. Interestingly, the periods 2008-2010 and 2020-2022, coinciding with the Great Financial Crisis and the Global Pandemic respectively, exhibit significant autocorrelation at various lags, indicating potential predictability during these turbulent economic times. The results suggest that stock returns undergo periods of independence and dependence, where predictability varies across different time frames and the null hypothesis H_{01a} is rejected in IBOVESPA market.

Panel D of Table 3.3 documented the autocorrelation coefficient of JSE All Share index (JALSH). The full sample possess no significant first order this indicate that a stock is predictable on the past price movement. However, significant autocorrelation at lag 5, 10, 15 and 20. The initial subsample period from 1993-1995, 1996-1998 and 2002-2004 show a significant auto correlation on various lag under consideration., implies dependent of stock return from the previous return. However, the sample period 1999-2001, 2005-2007,2008-2010, 2011-13,2017-19 show a no significant autocorrelation in any of the lags and the stock market was found to be independent. Thus, the behaviour of return appears to follow the EMH and can be categorised by type 2 categorization. The null hypothesis H_{01a} is rejected in JALSE market.

The autocorrelation results for the MOEX stock market, as documented in Panel E of Table 3.3, reveal full sample possesses significant autocorrelation at lag 5, 10, 15 and 20. The subsample period from 2002-2004 and 2008-2010 show a significant autocorrelation on various lags under consideration and the stock market show an independent return predictability in another subsample period. Overall, the MOEX stock market can be classified as an efficient market, displaying characteristics consistent with the Efficient Market Hypothesis (EMH) type classification.

Table 3.3: Result of Autocorrelation test for BRICS countries

Sample Period	Autocorrelation - Lags				
	1	5	10	15	20
Panel A: India (BSE Sensex)					
Full Sample	-0.025***	0.011	0.026*	0.008*	-0.016*
1990-1992	0.001	0.034	0.006	0.036**	0.051***
1993-1995	-0.125*	0.059**	0.075**	0.028**	0.037***
1996-1998	0.002	0.011	0.026*	0.008*	-0.016
1999-2001	-0.002	-0.016	0.018	-0.008	-0.102
2002-2004	-0.103**	-0.027***	0.047**	-0.06**	0.006**
2005-2007	0.006	0.007	0.045	0.006	-0.086
2008-2010	-0.031	-0.036	-0.002	0.001	-0.057
2011-2013	0.006	-0.015	0.015	0.013	-0.042
2014-2016	-0.053	-0.019	-0.046	-0.026	0.02
2017-2019	0.041**	-0.047	0.096**	0.072**	-0.008
2020-2022	0.070**	0.17*	0.047*	0.057*	0.048*
Panel B: China (SSE Composite)					
Full Sample	0.024***	0.043*	-0.001*	0.030*	0.005*
1990-1992	0.036	-0.066**	0.055***	0.017	0.035
1993-1995	0.063	-0.093**	-0.065**	-0.026**	-0.050**
1996-1998	0.02	0.037	0.018*	0.157*	0.013*
1999-2001	-0.058*	-0.014	-0.025	0.101*	0.109*
2002-2004	0.012	-0.03	0.006	-0.004	-0.067
2005-2007	-0.043*	-0.097**	0.125**	0.094*	-0.027*
2008-2010	-0.01	-0.015	0.003	0.058	-0.039
2011-2013	-0.012	0.024	0.054	-0.004	-0.03
2014-2016	-0.058	0.001**	-0.102*	0.025*	0.122*
2017-2019	0.006	-0.034**	0.047*	0.015**	0.051**
2020-2022	0.019	-0.032	0.016	-0.032	0.01
Panel C: Brazil (IBOVESPA)					
Full Sample	0.001	0.003*	0.012*	0.015*	0.027*
1990-1992	0.001	-0.008	0.002	0.006	0.02
1993-1995	0.006	0.008	-0.03**	0.029**	0.035*
1996-1998	-0.075**	-0.042*	0.075*	0.005**	0.047**
1999-2001	0.011	-0.046**	0.066**	0.063**	0.017
2002-2004	0.001	0.012	0.078	0.039	-0.019
2005-2007	-0.054	-0.029	0.029	0.017	0.048
2008-2010	-0.001	0.003***	0.041**	0.114**	0.081**
2011-2013	0.127	0.084	0.052	0.053	-0.01
2014-2016	0.002	0.017	0.023	0.008	0.03
2017-2019	-0.001	-0.114**	-0.013**	0.014	-0.019
2020-2022	0.104**	0.052**	0.046*	-0.066*	-0.069*
Panel D: South Africa (JALSH)					
Full Sample	0.001	-0.021**	-0.008*	0.014*	0.013*
1993-1995	0.031	-0.09	-0.059**	-0.114**	0.022
1996-1998	-0.007	0.017	-0.007	-0.008**	-0.024***
1999-2001	-0.007	-0.045	0.027	-0.004	0.027
2002-2004	-0.005	-0.034*	0.019**	-0.005	-0.013
2005-2007	0.001	-0.072	-0.009	0.006	-0.041
2008-2010	-0.014	-0.008	-0.021	0.067	0.068

2011-2013	-0.070	-0.064	-0.048	-0.024	-0.016
2014-2016	-0.079***	-0.042	-0.018	0.03	-0.054
2017-2019	0.043	-0.019	-0.097	0.044	0.079
2020-2022	0.011	0.015	0.004*	-0.024*	0.014*
Panel E: Russia (MOEX)					
Full Sample	-0.001	-0.026***	0.014***	0.014*	-0.048*
1996-1998	0.002	-0.137	0.066	-0.004	-0.189
1999-2001	0.003	0.032	0.027	0.048	0.039
2002-2004	-0.120*	0.012*	-0.050**	0.075**	-0.021
2005-2007	0.001	0.034	-0.028	0.031	0.011
2008-2010	-0.003	0.014	-0.029	0.022*	-0.011*
2011-2013	-0.002	-0.008	-0.053	-0.046	0.011
2014-2016	-0.031	-0.036	-0.014	-0.039	-0.007
2017-2019	-0.038	0.084	0.012	0.001	-0.044
2020-2022	0.004	0.007	-0.017	-0.052	0.005

Source: *Author's computation Using EViews*
Note(s): The test result of full sample and 3-year autocorrelation across BRICS countries. *, **, *** denotes a significant at 1%, 5% and 10% respectively.

3.4.2. Autocorrelation test result for G5 markets

The full sample in Table 3.4 exhibits significant negative first-order autocorrelation in the DAX 30, CAC 40, FTSE 100, and S&P 500 indices. This negative autocorrelation indicates a mean-reverting pattern or a tendency for stock prices to oscillate around their mean, suggesting predictability based on past price movements. The result of autocorrelation test in Table 3.4 also reports the coefficient for the subsample. In CAC 40, the result shows a first order autocorrelation for the sample period 2002-2004 and 2014-2016 show a negative significant, suggesting a mean-reverting pattern or a tendency for the series to oscillate around its mean. The initial three subsample period from 1990 to 1998 show a significant autocorrelation on various lag under consideration. However, the sample period 1990-2001 show no significant autocorrelation in any of the lags. The period 2002-2004 show a significant autocorrelation in all the lag and no significant the autocorrelation was found during in the subsequent sub-period of 2005-2007 subsample. This indicate that the stock return shows a period of independent and dependent during this period. Moreover, the subsample from 2008 to 2022 show a significant time varying return predictability. The result of the CAC suggest that the return undergoes through a period of independent and through a period of dependent. Thus, the behaviour of return appears to follow the AMH and can be categorised by type 4.

Panel B of Table 3.3 show the autocorrelation result of DAX 30 index return. The subsamples reveal distinct behaviours. The initial subsample from 1990-2000 shows no significant autocorrelation at various lags under consideration. Interestingly, the 1996-1998, 2008-2010 and 2020-2022 subsample displays significant autocorrelation at all lag, indicating predictability of stock returns during this period that are co-incident with the Asian Financial crisis, the Great depression and the Global pandemic. The subsamples 1993-1995 2002-2004, 2014-2016 and 2017-2019 exhibit significant autocorrelation at lags 5, 10, 15, and 20, indicating potential predictability. However, the subsample shows no significant autocorrelation on those subsequent years and show independence of stock returns during those periods. The alternating patterns of dependence and independence in stock returns suggest that the behaviour aligns with the AMH, where the market cycles between periods of efficiency (independence) and inefficiency (predictability), exhibiting varying degrees of predictability and independence over time.

Panel C of Table 3.3 show the autocorrelation result of FTSE 100 index return. The initial subsample from 1990-2000 shows a significant autocorrelation at 10, 15 and 20 lags. This implies that return series is not a purely random process and that there is some underlying pattern in the return. The 1996-1998, 1999-2001 and 2014-2016 subsample displays significant autocorrelation at all lag, indicating predictability of stock returns during this period. The subsamples 1993-1995 2005-2007, and 2011-2013 exhibit no significant autocorrelation at lags at all lags and 20, indicating potential unpredictability. The alternating patterns of dependence and independence in stock returns found to be significant suggest that the behaviour aligns with the AMH, where the market cycles between periods of efficiency (independence) and inefficiency (predictability), exhibiting varying degrees of predictability and independence over time.

Panel D of Table 3.3 show the autocorrelation result of Nikkei 225 index return. The overall sample period shows no significant autocorrelation implies that current return is not influence the previous stock return value. The alternating patterns of dependence (1990-1992, 1996-1998) and independence (1993-1995, 1999-2001, 2002-2004) in stock returns found to be significant suggest that the behaviour aligns with the AMH. The 1990-1992, 1996-1998, 2011-13 and 2020-2022 subsample displays significant autocorrelation at all lag, indicating predictability of stock returns during this period. And show no significant in other samples. The result suggests that the market cycles between periods of efficiency (independence) and inefficiency (predictability), exhibiting varying degrees of predictability and independence over time and classified as type 4 classification.

Panel E of Table 3.4 presents the autocorrelation coefficients for the S&P 500 index return. While the full sample does not exhibit significant first-order autocorrelation, it displays significant autocorrelation at all lags, indicating potential predictability based on past price movements. Considering the subsamples, the initial period from 1990-1992 does not show significant autocorrelation at any lag, suggesting independence of stock returns during this time frame. However, the subsamples of 1993-1995, 1999-2001, 2008-2010, 2011-2013, and 2020-2022 exhibit significant autocorrelation at various lags, implying predictability of stock returns during these periods. The results suggest that stock returns in the S&P 500 index undergo phases of independence, where returns are unpredictable based on past information, and phases of dependence, where returns exhibit predictability based on past price movements. This varying pattern of predictability across different time frames aligns with the notion that market efficiency is dynamic, with periods of efficiency and inefficiency coexisting.

Table 3.4: Result of Autocorrelation test for G5 countries

Sample Periods	Autocorrelation - Lags				
	1	5	10	15	20
Panel A: France (CAC 40)					
Full Sample	-0.021**	*-0.04**	*-0.003**	*0.008**	*0.005**
1990-1992	0.001	-0.053	0.093***	-0.015***	0.037***
1993-1995	0.006	-0.063	-0.006	-0.013**	-0.056**
1996-1998	0.002	0.018	0.063	0.023	*0.077**
1999-2001	-0.076	-0.023	0.046	0.072	0.03
2002-2004	-0.107*	-0.088**	-0.084*	0.066*	-0.032*
2005-2007	-0.002	-0.031	0.019	-0.019	0.03
2008-2010	-0.005	-0.065**	-0.013**	*-0.048**	-0.012**
2011-2013	-0.028	-0.055	-0.032	0.017	-0.007
2014-2016	-0.019***	-0.093**	-0.042***	-0.043**	0.039**
2017-2019	-0.007	-0.004	-0.031	0.034	0.031
2020-2022	0.001	0.057	-0.014*	0.018*	-0.007*

Panel B: Germany (DAX 30)					
Full Sample	-0.017**	-0.028**	0.019**	0.021**	0.025**
1990-1992	-0.068	-0.036	0.027	-0.054	0.011
1993-1995	0.010	-0.078	0.059***	-0.025**	0.003
1996-1998	-0.089**	0.038**	0.102*	0.094*	0.108*
1999-2001	0.002	-0.031	0.061	0.033	0.123**
2002-2004	0.002	-0.065	-0.082**	-0.02**	-0.058**
2005-2007	0.033	-0.049	0.021	-0.009	0.044
2008-2010	-0.002**	-0.038**	0.049***	-0.032	0.018***
2011-2013	-0.038	-0.063	-0.022	-0.009	0.025
2014-2016	-0.016	-0.093**	-0.062***	0.022**	0.046**
2017-2019	0.013	0.006	-0.046	-0.011	0.015
2020-2022	0.003***	0.076**	0.004**	-0.011*	-0.011*
Panel C: United Kingdom (FTSE 100)					
Full Sample	-0.036*	-0.033*	0.003*	0.01*	0.018*
1990-1992	-0.001	-0.015	0.091**	0.041**	0.065**
1993-1995	0.027	-0.013	-0.048	-0.056	-0.004
1996-1998	0.009**	-0.022**	0.009*	0.082*	0.066*
1999-2001	-0.129**	0.023**	-0.057**	-0.036**	0.046*
2002-2004	0.001	-0.031*	-0.049*	0.029**	-0.016
2005-2007	-0.011	-0.08	0.018	-0.031	-0.003
2008-2010	-0.005	-0.069*	0.038*	0.003*	-0.01*
2011-2013	0.001	-0.018	-0.041	0.037	0.005
2014-2016	-0.050*	-0.065*	-0.012**	-0.039*	0.087*
2017-2019	0.000	-0.021	-0.043	-0.015	-0.03
2020-2022	-0.003	0.071	0.017	0.056	0.025
Panel D: Japan (Nikkei 225)					
Full Sample	-0.001	-0.01	0.018	0.018	-0.017
1990-1992	-0.13**	0.012**	0.021**	0.029**	-0.025**
1993-1995	0.005	-0.083	-0.021	0.025	-0.073
1996-1998	-0.129**	0.021**	0.048*	-0.006**	-0.046**
1999-2001	-0.004	-0.005	0.043	0.029	0.001
2002-2004	-0.01	-0.016	-0.011	-0.04	-0.034
2005-2007	-0.023	0.047	0.06	0.006	0.033
2008-2010	-0.004	-0.066	0.057	0.024	-0.128
2011-2013	0.012**	0.059**	-0.074**	0.041**	0.013**
2014-2016	0.029	-0.02	0.016	0.001	0.033
2017-2019	0.001	0.022	0.01	0.056	-0.062
2020-2022	0.104**	-0.030**	-0.029**	-0.005**	-0.068**
Panel E: U.S (S&P 500)					
Full Sample	-0.014*	-0.021**	*0.005**	*-0.047**	*0.002**
1990-1992	-0.018	0.021	-0.024	-0.006	0.045
1993-1995	0.016	-0.056	-0.003	-0.051**	0.001**
1996-1998	-0.04	-0.039	0.068	0.001	-0.019
1999-2001	0.001	-0.079***	0.014	0.044**	-0.016**
2002-2004	-0.001	-0.02	-0.036	-0.075	-0.076**
2005-2007	-0.008	-0.026	0.09	-0.024	-0.026
2008-2010	-0.117	-0.028	0.023	-0.056**	0.071*

2011-2013	0.052*	-0.151*	0.076*	-0.002*	0.026*
2014-2016	-0.024	-0.014	-0.01	-0.096	0.07
2017-2019	-0.003	-0.05	-0.014**	-0.031**	-0.064**
2020-2022	0.123**	0.058**	-0.051**	-0.095**	-0.049**

Source: *Author's computation Using EViews*
Note(s): The test result of full sample and 3-years autocorrelation across G5 countries. *, **, *** denotes a significant at 1%, 5% and 10% respectively

3.4.3 Variance ratio test result for BRICS markets

The result of the variance ratio test for the BRICS stock markets are reported in Table 3.5. The BSE results shown in panel A of Table 3.5 represent the full sample and subsample under examination. The full sample show a positive correlation between returns for all four tested values of *k* lags, which is statistically significant at the 1%, 5%, and 10% levels for lags 2, lag 4, 16, and 8, respectively. The three joint tests i.e. CD, JR, JS shows a significant result, implying that stock returns in the full period are inefficient. The subsample analysis also provides evidence of a positive significant correlation for all tested k values. The subsamples for the periods 1993-1995, 1996-1998, 2011-13, 2014-16, and 2020-22 have certain *k'*s values greater than one and show statistical significance at least at the 10% level, suggesting that there is a positive serial correlation rather than a negative correlation, and the martingale hypothesis is rejected. The joint test in the BSE stock market indicates the rejection of the random walk hypothesis for almost all the subsample periods, except for the periods 1990-1992, 2008-2010, and 2019-2019. Therefore, the BSE market exhibits a tendency toward positive returns and has shifted from being positive to negative, with statistical significance. Hence, the BSE returns have followed an inefficient pattern throughout the observed period and have switched toward a more positive trend, suggesting a switch toward inefficient over the observed, indicating type 3 classification.

The estimated variance ratio test for SSEC represents in panel B of Table 3.5. The result of the full sample shows a positive correlation between returns for all four tested values of *k* (lags), which is statistically significant at the 1% level for lags 4 and 8, and at the 5% and 10% levels for lags 2 and 16, respectively. The three joint tests, CD, JR, and JS, show significant results, implying that stock returns in the full period are inefficient. Considering the subsample analysis, evidence of a positive significant correlation for all tested *k* values was found in the initial 1990-1992 period, indicating the rejection of the martingale hypothesis and, consequently, market inefficiency. The subsamples for the periods 1999-2001 and 2005-2017 have certain k values greater than one and exhibit statistical significance at least at the 10% level, suggesting the presence of a positive serial correlation rather than a negative correlation, and the rejection of the martingale hypothesis. The joint test results support the Lo and Mackinlay (VR) test and provide consistent findings. In contrast to the BSE results, the SSE exhibits a tendency toward positive returns and has shifted from being positive to negative, but without statistical significance. Hence, the SSE returns displayed an inefficient pattern initially and subsequently move toward efficiency over the observed period, indicating a type 2 classification.

The IBOVESPA result, as shown in panel C of Table 3.5, indicates that for the full sample has no significant martingale effect in returns for all four tested values of *k*. However, the joint test for JR and JS shows a significant result at the 1 percent level, implying that the stock returns in the full period are inefficient. The subsample analysis reveals a positive and significant martingale effect during 1993-1995, and a negative and significant martingale effect at 2005-2007, 2017-19, and 2020-22, with variance ratio values lower than one. This suggests that the market exhibits a tendency toward positive returns and has shifted from being positive to negative, with statistical significance. The joint test results for stock returns support the Lo and Mackinlay (VR) test and provide consistent findings. Hence, the IBOVESPA market is moving toward positive returns and has shifted from being positive to negative, with statistical significance. The results suggest that the independence of returns varies over time throughout the observed period, indicating type 3 classification.

The JALSH result as shown in panel D of Table 3.5, the full sample shows no significant martingale effect in return for tested values *k*=2 and *k*=4. The joint test for all tests shows a significance at 5 per cent, this implies that the stock return in the full period is inefficient and martingale effect was found to be rejected. Considering the subsample, the subsample provides there is a positive significance during 1996-1998, 1999-2004 and 2020-2022 and negative significance at 2014-2016 i.e., a value lower than one, suggesting that the market exhibits a tendency toward positive returns and has shifted from being positive to negative, with statistical significance. The joint test in stock return provides, test results support the Lo and Mackinlay (VR) test and provide consistent findings result in robustness of the test. Hence, the JALSH market is more toward positive and has shift from being positive to negative and are significant statistically. The result suggests that the return in independence varies overtime through the observed period and indicating type 4 classification.

According to panel E of Table 3.5, the full sample for the MOEX results shows a significant non-martingale effect in returns for the tested values of *k*=4 and *k*=6. The joint tests for JR and JS are significant at the 1 percent and 5 percent levels, respectively. This implies that stock returns over the full period are inefficient, and the null hypothesis of a martingale effect is rejected. When examining the subsamples, there is evidence of a positive and significant martingale effect during 1996-1998, 1999-2004, and 2004-2006, and a negative and significant martingale effect during 2011-2013, with variance ratio values less than one. This suggests that the market tends to exhibit positive returns but has transitioned from positive to negative, with statistical significance. The joint test results for stock returns corroborate the Lo and Mackinlay (VR) test findings, demonstrating the robustness of the test. The MOEX market leans more toward positive correlation returns but has shifted from positive to negative, with statistical significance. The results indicate that the independence of returns fluctuates over time throughout the observed period suggesting a type 4 classification or AMH market.

Table 3.5: Test result for the Lo & Mackinlay variance ratio test and Joint test for BRICS countries

	Lo & Mackinley (VR test)				**Joint test**		
	***k*=2**	***k*=4**	***k*=8**	***k*=16**	**CD**	**JR**	**JS**
Panel A: India (BSE Sensex)							
Full Sample	1.07*	1.10*	1.11**	1.18**	3.50**	9.68*	8.07*
1990-1992	1.05	1.12	1.19	1.36	1.36	1.78	6.95**
1993-1995	1.28*	1.34*	1.38*	1.43**	5.97*	8.27*	6.05*
1996-1998	1.09**	1.15**	1.18	1.26	2.20***	3.55**	3.99*
1999-2001	1.06	1.10	1.09	1.11	1.17	2.38**	1.97
2002-2004	1.05	1.00	1.07	1.18	0.66	2.22	2.87*
2005-2007	1.08	1.06	1.02	1.03	1.52	2.36**	3.42*
2008-2010	1.07	1.07	0.97	1.08	1.44	1.45	1.02

2011-2013	1.09**	1.08**	1.03	1.01	2.08**	2.48**	1.97
2014-2016	1.08**	1.10	1.08**	1.22**	2.20***	2.39**	2.17
2017-2019	1.06	1.10	1.02	0.98	1.05	1.07	1.85
2020-2022	1.09*	1.10	1.12**	1.11**	2.86**	2.41**	3.40*
Panel B: China (SSE Composite)							
Full Sample	1.03**	1.11*	1.26*	1.56***	8.85*	10.03*	11.21*
1990-1992	0.97**	1.02**	1.16**	1.38**	2.48**	20.26*	5.16*
1993-1995	0.99	1.07	1.16	1.19	0.77	0.79	0.77
1996-1998	0.98	1.03	1.11	0.92	0.62	1.45	0.94
1999-2001	1.03	1.04**	1.09**	1.13**	1.79***	2.27**	1.97**
2002-2004	1.01	1.03	1.03	0.99	0.35	0.84	1.50
2005-2007	1.01	1.00	1.25**	1.65*	1.02	3.97*	6.07*
2008-2010	1.00	1.01	1.07	1.10	0.56	1.20	0.52
2011-2013	0.99	0.98	0.96	1.03	0.40	0.61	0.48
2014-2016	1.07	1.06	1.15	1.25	1.24	0.58	1.59
2017-2019	0.98	1.04	1.01	1.06	0.47	0.83	0.78
2020-2022	1.02	1.04	0.96	0.82	0.93	1.52	1.93
Panel C: Brazil (IBOVESPA)							
Full Sample	0.98	1.06	1.10	1.14	1.17	3.45*	9.41*
1990-1992	0.99	1.06	1.11	1.13	0.96	1.21	5.15*
1993-1995	1.13**	1.17***	1.20**	1.62**	2.90*	4.52*	6.31*
1996-1998	1.06	1.01	0.92	1.02	0.83	1.71	2.09
1999-2001	1.03	1.07	0.92	0.95	0.45	1.29	0.96
2002-2004	1.04	1.01	1.00	1.05	0.99	1.65	1.20
2005-2007	1.01	0.95	0.82**	0.74**	1.56	2.55**	2.43**
2008-2010	0.98	0.87	0.75	0.72	1.32	1.04	0.59
2011-2013	1.00	0.98	0.95	0.94	0.40	0.64	0.51
2014-2016	0.99	0.99	0.95	0.92	0.48	0.83	1.24
2017-2019	0.97	0.92	0.84**	0.85**	2.43**	1.93**	1.52
2020-2022	0.80	0.85**	0.92	1.10	1.59	2.82**	1.58
Panel D: South Africa (JALSH)							
Full Sample	1.05**	1.07***	1.02	1.01	2.07**	4.84**	3.44**
1993-1995	1.10	1.18	1.24	0.53	1.13	1.47	1.15
1996-1998	1.12*	1.25	1.27	1.51**	1.64	5.08*	3.24
1999-2001	1.14**	1.27*	1.28***	1.27	2.64	5.04*	3.00*
2002-2004	1.10*	1.13***	1.03	1.07	2.81	3.09*	2.15***
2005-2007	0.98	0.98	0.90	0.73	1.19	1.58	2.09
2008-2010	1.04	1.00	0.87	0.82	0.86	0.88	0.47
2011-2013	1.04	1.00	0.87	0.82	0.86	0.88	0.47
2014-2016	0.98	0.90	0.81***	0.70**	1.60	1.35	1.04
2017-2019	0.99	1.05	1.10	0.94	0.86	0.96	0.83
2020-2022	1.00	1.04	1.04	1.06	0.31	2.15**	2.11***
Panel E: Russia (MOEX)							
Full Sample	1.06*	1.09***	1.05	1.06***	1.72	4.58*	2.39**
1996-1998	1.15*	1.24***	1.12	1.19	1.51	3.82*	3.30*
1999-2001	1.16*	1.21**	1.25**	1.48**	3.44*	4.99*	3.80*
2002-2004	1.08***	1.03	1.04	1.02	1.85	1.65	1.68
2005-2007	0.93	0.90	0.89	0.81	1.09	2.37	2.16
2008-2010	1.03	1.03	0.96	0.85	0.54	1.01	1.86
2011-2013	1.04**	1.01	0.93***	0.96	1.85***	1.84	1.64

2014-2016	1.01	0.97	1.01	0.99	0.21	1.09	1.27
2017-2019	1.00	0.96	1.02**	1.26***	0.38	1.19	2.53**
2020-2022	0.87	0.86	0.91	0.84	0.71	0.93	0.65

Source: *Author's computation Using EViews*
Note(s): The test result of full sample and 3-year Lo-Mackinlay Variance ratio test and Joint test of Chow-Denning (CD), Rank and Sign (JR and JS) across G5 countries. *k* is the number of lags of heteroscedastic test statistics. *, **, *** denotes a significant at 1%, 5% and 10% respectively. A p-value less than 0.10 implies the null hypothesis that an index return follows a random walk can be rejected at 10% level and accepting the alternative hypothesis of return serially correlated.

3.4.4 Variance ratio test result for G5 markets

The result of the variance ratio test for the G5 stock markets is reported in Table 3.6. In panel A of Table 3.6, the full sample indicates that the CAC 40 results show a positive correlation between returns for the tested values of *k* lags, which is statistically significant at the 5 per cent level for lags 4, 16, and 8, respectively. The three joint tests, namely CD, JR, and JS, show significant results, implying that stock returns in the full period are inefficient. When examining the subsamples, there is evidence of a negative significant martingale effect. The subsamples for the periods 1993-1995, 2002-2004, 2005-2007, 2008-2010, and 2011-2013 have certain k values less than one and show statistical significance at least at the 10 percent level, suggesting that there is a negative serial correlation, and the martingale hypothesis is rejected. This implies that the movement of the previous stock price has a serial correlation effect on the future movement. The joint tests demonstrate the robustness of the test and indicate the rejection of the random walk hypothesis for the subsample periods. Therefore, the CAC 40 market exhibits a tendency toward negative returns and has shifted from being positive to negative, though not necessarily statistically significant. Hence, the CAC 40 returns followed an inefficient pattern throughout the observed period and have switched toward a more negative trend, suggesting a shift toward inefficiency overtime during the observed period, indicating type 3 classification.

The DAX 30 results, as shown in panel B of Table 3.6, show there is a significant non-martingale effect in returns for the tested values of *k*=2 and *k*=4 in the full sample. The joint tests for JS and JR show significance at the 5 percent level, implying that the stock returns in the full period are inefficient, and the martingale effect is rejected. Considering the subsamples, there is a positive significant effect during 2020-2022 at lag 10 and a negative significant effect during 2002-2004, suggesting that the market exhibits serial correlation with positive and negative periods during those times. The joint tests for stock returns show that the martingale effect was rejected in 2005-2007, 2011-2013, and 2020-2023. Hence, the DAX market is more inclined towards an efficient market, indicating type 2 classification.

The FTSE 200 results in panel C of Table 3.6 indicate a significant non-martingale effect in returns for all tested lags (*k* values) in the full sample. The three joint tests show significance at the 5% level, implying inefficient stock returns in the full period, and the martingale hypothesis is rejected. For subsamples, there was a positive significant effect before the 2000s (1990-1992 and 1996-1998) and a negative significant effect during 2005-2007, 2008-2010, and 2020-2022, suggesting serial correlation with positive and negative periods. The joint tests demonstrate the rejection of the random walk hypothesis for those subsamples. The FTSE 100 market exhibits a tendency toward negative returns, shifting from positive to negative, though not necessarily statistically significant. Overall, the DAX 30 returns followed a time varying return inefficient pattern throughout the observed period, indicating type 4 classification.

The Nikkei 225 results, as shown in panel D of Table 3.6, indicate that the full sample has significant non-martingale effect in returns for the tested values of *k*=4 and *k*=8. The three joint tests for all show significance up to 10 percent level, implying that the stock returns in the full period are inefficient, and the martingale effect is rejected. Considering the subsamples, the result provides a negative significant serial correlation during 1996-1998, 2005-2007 and 2017-2019 at lag certain lag value, suggesting that the market exhibits oscillatory trend or mean reversal pattern. The joint tests for stock returns show that the martingale effect was rejected in 1993-1995, 1996-1998, 2005-2007,2017-2019, and 2020-2022. Hence, the Nikkei 225 market is switch towards an efficient and inefficient market, classified as type 3 switch to inefficient.

The S&P 500 results, as shown in panel E of Table 3.6, indicate a significant non-martingale effect in returns for the tested lag values (*k*) in the full sample. The three joint tests show significance up to the 5 percent level, implying inefficient stock returns in the full period, and the martingale effect is rejected. Considering the subsamples, the results provide evidence of negative significant serial correlation during 2005-2007, 2008-2010, and 2017-2019 at certain lag values, suggesting that the market exhibits an oscillatory trend or mean-reversal pattern. The joint tests for stock returns show that the martingale effect was rejected in 1993-1995, 1996-1998, 2005-2007, 2008-2010, 2014-2016, and 2020-2022. The joint tests signify that the S&P 500 exhibits time-varying return predictability. Hence, the S&P 500 market switches between efficient and inefficient periods across at least three different periods, classified as type 4, i.e., the Adaptive Market Hypothesis (AMH).

Table 3.6: Test result for the Lo & Mackinlay variance ratio test and Joint test for G5 countries

	Lo & McKinley (VR test)				**Joint test**		
	***k*=2**	***k*=4**	***k*=8**	***k*=16**	**CD**	**JR**	**JS**
Panel A: France (CAC 40)							
Full Sample	0.99	0.95**	0.89**	0.85**	1.97***	*3.21**	*3.21**
1990-1992	1.04	1.05	1.10	1.15	0.90	1.27	1.06
1993-1995	1.01	1.02	0.98	0.88***	0.72	1.70	1.96**
1996-1998	1.06	1.03	0.99	0.99	1.16	1.52	0.87
1999-2001	1.022	0.95	0.87	0.85	1.05	1.49	0.80
2002-2004	0.99	0.93	0.75**	0.69	1.58	2.31**	1.54
2005-2007	0.94**	*0.88**	*0.80**	*0.73**	1.49	*3.21**	*3.95**
2008-2010	0.93	0.79**	0.76	0.70	1.98***	1.19	0.27
2011-2013	0.92**	0.88***	0.81***	0.76	1.27	2.32**	2.24**
2014-2016	1.00	0.99	0.88	0.75	1.27	1.17	1.15
2017-2019	1.04	1.05	1.01	0.95	0.83	0.64	1.21
2020-2022	0.98	1.07	1.18	1.23	0.94	1.33	1.44
Panel B: Germany (DAX 30)							
Full Sample	0.99**	0.97**	0.94	0.93	1.14	2.47**	2.78**
1990-1992	1.00	0.97	1.00	0.99	0.26	1.35	0.88
1993-1995	1.01	1.00	0.97	0.93	0.43	1.50	1.73
1996-1998	1.04	0.94	0.93	0.94	0.83	1.69	0.85
1999-2001	1.00	0.99	1.01	0.99	0.10	1.11	0.81
2002-2004	0.94	0.91**	0.81**	0.83	1.28	1.97	1.84
2005-2007	0.97	0.99	0.89	0.82	0.99	2.64**	0.99
2008-2010	0.96	0.87	0.88	0.84	1.23	0.56	0.91
2011-2013	1.10	1.08	0.95	0.98	2.11**	1.36	0.81
2014-2016	0.99	1.02	0.97	0.86	0.72	0.56	0.73
2017-2019	0.97	0.99	0.96	0.87	0.73	1.45	1.06
2020-2022	0.97	1.05**	1.16	1.26	0.96	1.79	2.11
Panel C: United Kingdom (FTSE 100)							
Full Sample	0.98**	0.93**	0.88**	0.84**	2.05**	3.46*	2.76**
1990-1992	1.04	1.09**	1.18	1.24	1.43	0.37	1.89***
1993-1995	1.04	1.10	1.08	1.03	1.50	1.24	1.05
1996-1998	1.09**	1.04	0.94	0.90	2.12***	2.11***	1.40
1999-2001	1.05	0.93	0.83	0.78	1.33	1.78	1.93***

2002-2004	0.94	0.88	0.76	0.72	1.33	2.29**	1.74
2005-2007	0.90**	0.84	0.74	0.64	1.75	2.18**	1.31
2008-2010	0.93	0.81**	0.80	0.79	1.73	1.30	1.03
2011-2013	1.03	0.98	0.87	0.78	1.01	1.79	0.18
2014-2016	1.03	1.03	0.92	0.73	1.19	1.42	1.67
2017-2019	1.02	1.02	0.95	0.90	0.53	0.93	0.399
2020-2022	0.95*	0.92**	0.98	1.02**	0.74	3.18**	2.58**
Panel D: Japan (Nikkei 225)							
Full Sample	0.97	0.93***	0.88**	0.89	1.99***	2.55**	2.88**
1990-1992	1.05	0.95	0.92	0.99	1.17	1.76	1.27
1993-1995	0.99	0.99	0.93	0.95	0.52	1.46	2.16**
1996-1998	0.91***	0.78**	0.69**	0.75	2.32**	2.64**	2.65**
1999-2001	0.95	0.89	0.83	0.83	1.42	1.38	1.09
2002-2004	1.01	1.02	1.02	0.91	0.52	1.00	0.74
2005-2007	0.99***	0.99	0.99	0.95	0.21	0.21	1.69
2008-2010	0.94	0.86	0.78	0.80	1.00	1.67	1.81
2011-2013	0.96	0.98	0.95	1.01	0.57	1.63	1.87
2014-2016	0.93	0.91	0.82	0.74	1.31	1.12	1.37
2017-2019	0.92**	0.88**	0.93	0.88	1.93	2.21**	2.04**
2020-2022	1.02	1.12	1.13	1.14	1.00	0.68	2.79**
Panel E: U.S (S&P 500)							
Full Sample	0.92*	0.87**	0.80*	0.77**	3.30**	5.09*	3.09**
1990-1992	1.06	1.06	1.06	1.05	1.54	1.23	1.82
1993-1995	1.02	1.016	0.85	0.76	1.43	2.25***	1.20
1996-1998	0.99	0.95	0.87	0.83	0.74	2.11***	1.85
1999-2001	1.01	0.93	0.84	0.77	1.29	1.92	1.83
2002-2004	0.95	0.93	0.85	0.85	0.95	2.38***	2.18***
2005-2007	0.88*	0.81**	0.69**	0.59**	2.80**	3.39*	2.91**
2008-2010	0.87*	0.75**	0.70***	0.69	2.27***	2.71**	2.22***
2011-2013	0.93	0.89	0.75	0.69	1.25	1.85	1.05
2014-2016	0.99	0.96	0.86	0.74	1.15	2.09**	3.28*
2017-2019	0.96	0.93	0.91	0.81	0.76	1.58	1.27
2020-2022	0.78**	0.83*	0.81	0.85*	2.19***	1.69	1.78

Source: *Author's computation Using EViews*

Note(s): The test result of full sample and 3-year Lo-Mackinlay Variance ratio test and Joint test of Chow-Denning (CD), Rank and Sign (JR and JS) across G5 countries. k is the number of lags of heteroscedastic test statistics. *, **, *** denotes a significant at 1%, 5% and 10% respectively. A p-value less than 0.10 implies the null hypothesis that an index return follows a random walk can be rejected at 10% level and accepting the alternative hypothesis of return serially correlated.

3.5. Empirical result for nonlinearity test

In this section, we present the empirical results related to nonlinearity. To examine the presence of nonlinear dependence, we conducted a series of nonlinear tests to ensure that our empirical findings are not overly sensitive to the specific test employed. The Ljung-Box test statistic, as shown in the Appendix-I (Table 1 and Table 2), indicates a significant autocorrelation structure, suggesting that linearity tests cannot be reliably performed. To conduct these nonlinearity tests, we first removed any linear dependence from the data by fitting an AR(*p*) model. This step ensures that any remaining patterns detected can be attributed to nonlinear dynamics rather than linear structures. The pre-whitening autoregressive (AR) model investigates the existence of nonlinear structures in the stock market returns. These AR models act as filters, removing any linear relationships present in the data, thereby allowing us to examine the nonlinear components of the returns exclusively. The identified and estimated AR models are presented in Appendix-I (Table 1 and Table 2), with the model diagnostics confirming the successful elimination of linear structures. Three tests to assess the presence of nonlinearity in the residuals obtained from the AR models: the McLeod-Li statistics (Qrr(*k*)) of the squared AR residuals, the Engle LM test statistics, which also examines the nonlinear dependence in the filtered returns, and the BDS test statistics. The inclusion of the BDS test statistics enhances the robustness of our testing approach by incorporating an additional measure specifically designed to detect nonlinear patterns.

The empirical findings presented in Tables 3.7 and 3.8 provide compelling evidence of significant nonlinear dependence in stock market returns, even after accounting for and removing linear dependence through the use of an AR(*p*) model. Notably, while linear dependence exhibited fluctuations over time, the nonlinear dependence appears to be consistently present throughout the sample periods analysed. In the case of the SSE, nonlinear independence was found in the sample periods 1990-1992 and 2011-2013. The IBOVESPA stock returns exhibit nonlinear independence across the whole sample period and the 1990-1992 period also displays nonlinear independence. The nonlinearity dependence is found to be significant in almost all the sample periods for BRICS and G5 countries. Comparing developing and developed countries, the nonlinearity dependence is stronger in developed countries. This consistency suggests that the nonlinear dependence inherent in each return series is robust and can be characterized as a type 5 classification, indicating a strong and persistent nonlinear inefficiency.

Table 3.7: Test results for the nonlinearity dependence on the AR-filtered Stock return for BRICS countries

		Ljung-Box Test statistics			McLeod-Li Test Statistics			Engel L-M test statistics		
	AR	**Q(5)**	**Q(10)**	**Q(20)**	**Qrr(5)**	**Qrr(10)**	**Qrr(20)**	**Lag 5**	**Lag 10**	**Lag 20**
Panel A: India (BSE Sensex)										
Full Sample	17	0.01	0.02	5.05	1943.30*	3306.30*	4756.80*	234.57*	142.60*	75.34*
1990-1992	0	5.64	9.76	20.07	156.78*	248.91*	408.66*	21.73*	10.36*	8.43*
1993-1995	2	2.53	8.66	19.01	46.68*	81.45*	143.32*	7.85*	5.41*	4.04*
1996-1998	3	1.16	6.91	25.24	23.58*	33.16*	61.33*	3.83*	2.05**	2.82*
1999-2001	1	5.27	12.88	26.91	101.46*	129.18*	155.93*	14.13*	7.85*	4.78*
2002-2004	4	0.47	3.76	12.88	210.99*	225.50*	233.35*	61.04*	31.52*	15.91*
2005-2007	2	0.35	7.32	20.57	243.51*	308.50*	531.31*	30.80*	16.00*	10.30*
2008-2010	1	3.89	14.34	25.36	69.50*	140.17*	201.03*	10.62*	8.09*	4.26*
2011-2013	3	0.06	1.84	12.96	23.35*	74.38*	135.91*	4.82*	6.16*	4.00*
2014-2016	3	1.55	6.53	11.18	11.26**	25.83*	35.24**	2.34**	2.40*	1.65**
2017-2019	3	1.40	12.39	20.31	45.10*	49.76*	80.09*	8.10*	4.13*	2.94**
2020-2022	7	0.80	1.80	20.12	272.10*	676.94*	676.94*	46.91*	46.69*	28.66*
Panel B: China (SSE Composite)										
Full Sample	15	0.01	0.02	5.01	20.23*	25.09*	28.17*	3.72*	2.20*	1.99*
1990-1992	0	8.60	16.51	23.91	0.11	0.35	0.41	0.02	0.03	0.02
1993-1995	6	0.33	8.34	18.63	110.17*	125.86*	127.65*	17.66*	9.37*	4.67*
1996-1998	9	0.01	0.61	26.85	138.95*	153.36*	178.06*	21.20*	8.51*	6.41*
1999-2001	3	0.26	7.85	37.97	45.56*	67.25*	113.73*	7.34*	4.11*	3.07*
2002-2004	0	0.93	5.18	12.30	46.98*	63.33*	73.94*	9.02*	4.96*	1.00
2005-2007	6	0.18	1.62	29.20	23.29*	27.20*	74.32*	3.69*	2.09*	2.43*
2008-2010	0	3.40	5.81	17.93	37.66*	88.47*	117.21*	5.93*	5.38*	3.16*
2011-2013	0	2.07	11.56	15.90	2.79**	10.96*	14.76*	0.54	1.16	0.87
2014-2016	8	0.22	3.50	5.83	176.88*	225.31*	368.51*	21.16*	10.81*	6.78*
2017-2019	7	0.09	3.24	11.44	31.47*	79.58*	96.06*	5.32**	5.48**	3.28**
2020-2022	1	3.54	6.92	12.38	19.32*	31.80*	43.46*	3.21**	2.59**	3.50*

Panel C: Brazil (IBVESPA)										
Full Sample	3	1.37	3.19	14.59	0.73	0.73	0.73	0.15	0.07	0.04
1990-1992	0	1.48	1.60	1.98	0.01	0.03	0.07	2.10**	7.34*	3.18**
1993-1995	9	0.45	1.41	18.84	132.07*	178.80*	200.92*	17.99*	11.07*	5.86*
1996-1998	9	0.13	3.41	17.78	231.42*	403.54*	502.82*	35.85*	24.82*	13.53*
1999-2001	5	0.28	6.24	15.73	21.13*	28.22*	28.65*	2.87**	14.70*	1.95**
2002-2004	0	2.76	9.88	23.17	33.28*	71.16*	115.54*	5.45*	4.63*	3.64*
2005-2007	0	5.18	8.58	17.94	27.06*	51.16*	65.17*	5.58*	4.66*	2.73*
2008-2010	3	0.09	7.79	19.65	347.70*	749.04*	1299.40*	32.71*	41.15*	26.12*
2011-2013	0	0.86	3.08	16.21	84.57*	94.21*	116.71*	13.67*	7.22*	4.08*
2014-2016	1	3.32	9.57	12.32	36.10*	70.44*	140.88*	5.99*	4.99*	3.76*
2017-2019	7	0.01	0.73	6.73	4.82*	3.95*	8.12*	4.15**	3.86*	7.56*
2020-2022	8	0.25	0.63	20.49	321.38*	476.32*	555.39*	38.60*	38.92*	20.53*
Panel D: South Africa (JALSH)										
Full Sample	7	0.01	1.61	23.15	2206.30*	3264.30*	4230.00*	261.90*	142.77*	72.83
1993-1995	1	3.18	15.87	24.36	18.43*	34.57*	39.21*	5.04*	4.90*	2.64*
1996-1998	4	0.62	4.92	20.06	244.78*	254.17*	266.32*	54.61*	27.94*	13.78*
1999-2001	2	2.15	6.04	15.01	58.85*	82.64*	88.09*	10.39*	7.28*	4.01*
2002-2004	3	0.30	2.20	6.12	31.34*	40.70*	61.99*	5.59*	3.31**	2.49**
2005-2007	0	5.43	6.37	23.89	235.46*	295.53*	370.86*	28.50*	15.90*	8.65*
2008-2010	3	1.30	5.99	16.18	243.24*	554.97*	946.85*	35.21*	28.21*	17.61*
2011-2013	0	8.30	13.89	26.60	72.88*	121.16*	213.05*	12.19*	8.08*	5.23*
2014-2016	2	2.65	4.08	12.78	42.12*	97.50*	171.09*	6.08*	5.90*	4.08*
2017-2019	0	2.57	11.76	22.81	24.64*	48.23*	68.55*	4.22*	3.46*	2.02**
2020-2022	8	0.03	0.36	27.52	371.26*	557.44*	630.74*	67.14*	36.23*	18.54*
Panel E: Russia (MOEX)										
Full Sample	14	0.01	0.04	16.56	886.25*	1084.60*	1829.10*	130.78*	69.15*	40.26*
1996-1998	1	6.82	9.25	27.06	58.86*	59.22*	94.10*	10.77*	5.25*	3.07*
1999-2001	1	4.16	11.53	24.59	61.92*	76.49*	96.50*	8.90*	4.79*	2.85*
2002-2004	3	0.56	3.11	11.04	61.18*	75.66*	89.64*	9.05*	5.29*	3.19**
2005-2007	1	2.73	4.04	19.56	223.34*	277.12*	479.16*	28.80*	15.83*	11.01*

2008-2010	1	3.89	9.52	40.37	116.17*	166.94*	490.96*	19.86*	10.81*	11.89*
2011-2013	0	4.86	9.44	19.39	44.69*	120.37*	160.07*	6.74*	8.02*	4.48*
2014-2016	0	1.76	5.59	14.61	24.10*	42.42*	43.98*	4.94*	3.60*	1.76*
2017-2019	0	8.05	10.18	22.47	19.93*	25.35**	28.01***	4.00*	2.41***	1.35
2020-2022	1	3.25	11.56	20.39	16.39*	17.95**	18.18**	2.89**	1.55	0.76

Source: *Author's computation Using EViews*

Note(s): The Ljung-Box Q(k) test statistic was computed at multiple lag lengths (5, 10, and 20) to ensure the robustness of the nonlinearity dependence tests applied to the stock returns data. The Qss(k) represents the McLeod-Li test, which evaluates the null hypothesis that the increments follow an independent and identically distributed (i.i.d) process. the Engle Lagrange Multiplier (LM) test statistics were examined to assess the presence of heteroscedasticity, or non-constant variance in the data series. *, **, *** denote significant at 1%, 5% and 10% level respectively.

Table 3.8: Test results for the nonlinearity dependence on the AR filtered Stock return for G5 countries

		Ljung-Box Test statistics			**McLeod-Li Test statistics**			**Engel L-M test statistics**		
	AR	**Q(5)**	**Q(10)**	**Q(20)**	**Qrr(5)**	**Qrr(10)**	**Qrr(20)**	**Lag 5**	**Lag 10**	**Lag 20**
Panel A: France (CAC 40)										
Full Sample	6	0.00	2.43	18.95	2034.60*	3458.10*	5056.70*	268.21*	151.59*	79.22*
1990-1992	5	0.02	10.33	23.05	74.80*	95.65*	103.30*	10.53*	6.15*	3.17*
1993-1995	0	3.52	12.10	33.04	2.31*	12.51*	21.63*	0.44	1.16	1.00
1996-1998	7	0.06	3.20	17.20	170.99*	274.73*	418.12*	20.83*	13.63*	7.97*
1999-2001	2	0.54	8.30	18.95	36.71*	101.91*	125.47*	6.54*	7.92*	4.66*
2002-2004	6	0.08	7.78	29.43	253.00*	540.25*	1026.10*	31.08*	21.99*	13.13*
2005-2007	1	2.21	6.69	11.16	109.25*	197.29*	288.00*	14.70*	9.42*	5.38*
2008-2010	5	0.15	7.38	15.07	195.04*	285.30*	474.11*	25.64*	15.06*	10.39*
2011-2013	5	0.02	2.34	8.95	140.27*	213.15*	362.85*	22.13*	12.49*	8.32*
2014-2016	5	0.04	2.52	14.67	56.81*	79.77*	87.82*	8.56*	5.15*	2.64**
2017-2019	0	2.54	5.25	18.23	39.81*	49.56*	56.59*	6.60*	3.94*	2.18**
2020-2022	8	0.02	0.26	22.59	158.74*	247.64*	281.58*	30.99*	20.41*	11.04*
Panel B: Germany (DAX 30)										
Full Sample	6	0.01	0.36	20.69	1874.10*	3480.50*	5392.10*	256.88*	158.49*	84.96*

1990-1992	0	3.69	14.38	20.57	42.33*	47.84*	57.59*	7.31*	3.78*	2.21**
1993-1995	0	5.81	15.60	26.53	19.55*	51.98*	71.65*	3.66*	3.95*	2.29*
1996-1998	7	0.11	4.76	27.75	212.49*	423.10*	655.99*	24.89*	16.83*	11.77*
1999-2001	0	2.82	8.79	28.85	103.68*	219.58*	237.43*	21.21*	15.47*	8.34*
2002-2004	1	4.31	19.78	35.01	273.04*	563.60*	980.77*	34.74*	22.44*	12.48*
2005-2007	0	4.61	6.76	12.81	60.82*	123.18*	169.42*	9.50*	7.79*	4.33*
2008-2010	4	1.12	6.84	17.32	162.20*	258.29*	505.29*	22.84*	16.62*	14.25*
2011-2013	5	0.02	3.40	17.03	192.08*	332.25*	591.08*	25.65*	15.61*	9.67*
2014-2016	5	0.09	5.00	16.10	50.93*	87.23*	101.29*	7.57*	5.66*	3.11*
2017-2019	0	6.63	9.28	17.75	24.86*	30.15*	47.64*	4.45*	2.61**	2.04**
2020-2022	8	0.06	0.39	20.39	96.17*	189.50*	231.47*	19.94*	18.13*	10.25*
Panel C: United Kingdom (FTSE 100)										
Full Sample	17	0.01	0.03	5.23	2549.90*	4334.40*	6250.10*	334.52*	196.64*	103.22*
1990-1992	7	0.09	7.74	23.35	18.23*	23.34*	48.53*	3.06*	2.09**	1.94*
1993-1995	0	0.89	6.11	17.96	14.50*	26.01*	76.12*	2.83*	2.03**	2.74*
1996-1998	9	0.43	2.00	23.93	95.01*	200.26*	361.22*	12.95*	11.07*	6.62*
1999-2001	2	1.67	4.30	18.40	87.83*	135.55*	149.59*	13.08*	7.47*	4.40*
2002-2004	7	0.06	3.21	10.10	303.22*	562.85*	852.35*	33.97*	23.05*	12.79*
2005-2007	1	5.19	8.24	15.99	201.09*	311.61*	396.72*	25.65*	14.18*	7.80*
2008-2010	9	0.28	2.42	12.82	249.07*	381.97*	625.89*	34.24*	20.87*	13.0*
2011-2013	0	6.42	9.73	14.91	174.49*	296.78*	492.59*	21.47*	13.43*	8.15*
2014-2016	5	0.06	3.26	21.18	246.97*	298.25*	344.44*	32.30*	16.59*	9.09*
2017-2019	0	2.33	5.98	8.42	32.13*	34.56*	46.63*	5.75*	2.97**	2.01**
2020-2022	8	0.06	0.61	24.30	137.31*	243.83*	303.9*7	24.49*	21.23*	11.53*
Panel D: Japan (Nikkei 225)										
Full Sample	2	2.26	8.35	21.85	2401.90*	3873.90*	5431.10*	290.20*	166.62*	87.38*
1990-1992	2	0.45	8.72	17.50	50.98*	60.56*	76.08*	7.64*	3.91*	2.47**
1993-1995	0	5.83	7.43	28.17	39.13*	52.34*	67.55*	7.42*	4.09*	2.33**
1996-1998	4	0.69	8.91	23.20	72.78*	116.74*	215.64*	10.70*	6.47*	4.12*
1999-2001	1	1.19	11.12	16.48	43.66*	66.43*	98.07*	8.30*	5.48*	3.60*

2002-2004	0	1.00	10.33	16.95	25.39*	57.83*	75.95*	5.26*	5.12*	2.98**
2005-2007	1	6.09	10.46	17.21	43.25*	67.69*	115.23*	6.21*	3.82*	2.64*
2008-2010	1	6.09	10.35	19.20	543.63*	884.31*	1220.10*	79.19*	46.85*	25.21*
2011-2013	9	0.08	3.84	15.53	81.53*	87.54*	96.68*	15.07*	7.93*	4.76*
2014-2016	1	3.95	5.44	16.95	52.42*	71.14*	119.13*	8.58*	5.14*	3.81*
2017-2019	1	4.80	12.82	25.24	39.72*	58.89*	78.43*	7.41*	5.00*	2.87*
2020-2022	3	0.77	9.73	25.72	217.81*	412.37*	510.59*	40.47*	25.77*	13.65*
Panel E: U.S (S&P 500)										
Full Sample	8	7.85	12.63	36.77	8.69**	9.86**	20.920**	1.667	0.940	0.951
1990-1992	1	1.53	8.52	19.24	38.93*	58.31*	88.62*	6.103*	3.75*	2.83*
1993-1995	0	7.85	12.63	36.77	8.69*	9.86*	20.92*	1.667	0.940	0.951
1996-1998	0	2.43	11.32	33.46	91.53*	109.91*	135.61*	15.32*	8.46*	4.72*
1999-2001	5	0.04	3.35	24.54	24.75*	32.91*	46.03*	4.12*	2.52*	1.77*
2002-2004	0	0.94	9.91	33.67	299.82*	534.17*	825.14*	43.44*	24.83*	13.48*
2005-2007	1	4.25	16.48	23.89	76.358*	200.99*	291.56*	13.99*	13.62*	7.25*
2008-2010	3	0.56	3.84	22.80	308.88*	603.29*	1038.70*	51.33*	31.52*	19.50*
2011-2013	5	0.09	8.05	23.36	268.98*	369.10*	512.54*	46.89*	26.69*	14.48*
2014-2016	0	4.64	8.12	21.47	225.27*	277.35*	291.43*	28.80*	14.97*	8.02*
2017-2019	8	0.03	1.92	20.26	114.65*	209.24*	272.06*	14.78*	12.03*	6.50*
2020-2022	9	0.04	1.26	4.15	417.12*	686.12*	775.33*	53.40*	31.71*	17.01*

Source: *Author's computation Using EViews*

Note(s): The Ljung-Box Q(k) test statistic was computed at multiple lag lengths (5, 10, and 20) to ensure the robustness of the nonlinearity dependence tests applied to the stock returns data. The Qss(k) represents the McLeod-Li test, which evaluates the null hypothesis that the increments follow an independent and identically distributed (i.i.d) process. The Engle Lagrange Multiplier (LM) test statistics were examined to assess the presence of heteroscedasticity, or non-constant variance in the data series. *, **, *** denote significant at 1%, 5% and 10% level respectively.

3.5.1. BDS test result for BRICS markets

The empirical results of the BDS test for BRICS countries for the AR-filtered and the AR-GARCH filtered return over the full sample period and the subsample period are presented in Table 3.9. The nonlinear dependence examine was conducted after removing linear dependence through an AR(p) model and residual fitted of the GARCH (1,1) model. The BDS test results reveal significant nonlinear dependence in stock returns across BRICS markets, even after accounting for linear dependence through AR filtering and conditional heteroscedasticity AR-GARCH filtering. For the Indian BSE market shown in Panel A of Table 3.9, nonlinear dependence is evident in the full sample and most sub-periods, except 2011-2013 and 2014-2016. AR-GARCH filtering reduces but does not eliminate nonlinear dependence, suggesting conditional heteroscedasticity as a primary source. The Chinese SSE Composite index in Panel B of Table 3.9 exhibits nonlinear dependence throughout, with some sub-periods like 2002-2004, 2011-2013, and 2020-2022 showing temporary independence. Residual nonlinearity persists after AR-GARCH filtering in certain sub-periods, indicating alternating episodes of independence and dependence, consistent with the Adaptive Market Hypothesis (AMH) and a type 4 classification. The IBOVESPA in Panel C of Table 3.9 returns display nonlinear dependence across the full sample, with intermittent periods of independence in subperiods like 2002-2004, 2005-2007, 2014-2016, and 2017-2019. AR-GARCH filtering fails to eliminate nonlinearity in specific sub-periods, again suggesting an AMH-type 4 behaviour. Panel D of Table 3.9 reports JALSH, nonlinear dependence is observed in the full sample, with temporary independence in 2002-2004 and 2017-2019. Residual nonlinearity after AR-GARCH filtering is detected in sub-periods like 1996-1998, 2008-2010, and 2014-2016, indicating a potential type 3 classification with switching market efficiency. Finally, panel D of Table 3.9 shows MOEX exhibits nonlinear dependence throughout the full sample. While AR filtering rejects nonlinearity in all sub-periods, AR-GARCH filtering reveals residual nonlinearity in 1996-1998, 2002-2004, 2017-2019, and 2020-2022, suggesting a type 4 classification with alternating episodes of independence and dependence and the null hypothesis of H_{04a} is rejected.

Table 3.9: BDS test result on AR filtered and AR-GARCH filtered stock return for BRICS Countries

	AR filtered on stock return					Residual fitted of the GARCH model				
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Panel A: India (BSE Sensex)										
Full Sample	17	0.0132*	0.0577*	0.1307*	0.1774*	17	0.0595*	0.1122*	0.1676*	0.1558*
1990-1992	0	0.0088*	0.0265*	0.0999*	0.1556*	0	-0.0007	-0.0015	-0.0008	-0.0052
1993-1995	2	0.0059*	0.0286*	0.0709*	0.0884*	2	0.0003	0.0018	0.0033	0.0015
1996-1998	3	0.0027*	0.0108*	0.0260*	0.0462*	3	0.0004	-0.0008	0.0003	-0.0016
1999-2001	0	0.0100*	0.0361*	0.0729*	0.1165*	0	0.0013	0.0025	0.0033	0.0086
2002-2004	4	0.0038*	0.0213*	0.0618*	0.0993*	4	-0.0009	-0.0021	-0.0023	0.0029
2005-2007	2	0.0131*	0.0512*	0.1098*	0.1479*	2	0.0015**	0.0053***	0.0066	-0.0010
2008-2010	1	0.0155*	0.0632*	0.1483*	0.1796*	1	-0.0006	-0.0056**	-0.0003	0.0012
2011-2013	3	0.0003	0.0088	0.0229	0.0467*	3	-0.0018**	-0.0040**	-0.0056	-0.0054
2014-2016	3	-0.0028	0.0016	0.0054	0.0158	3	-0.0040**	-0.0034	-0.0058**	-0.0098
2017-2019	3	0.0044*	0.0145*	0.0343*	0.0709*	3	0.0012	-0.0007	-0.0049	-0.0062
2020-2022	7	0.0102*	0.0472*	0.1031*	0.1480*	7	0.0022	0.0040	0.0003	-0.0029
Panel B: China (SSE Composite Index)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	15	0.0171*	0.0759*	0.1581*	0.1671*	15	0.0061**	0.0046	0.1214**	0.1879**
1990-1992	0	0.0161*	0.059*	0.151*	0.175*	0	-0.0004	0.001537	0.000371	-0.0019
1993-1995	6	0.0723*	0.1309*	0.2128*	0.1848*	6	0.0008	-0.0173	-0.0526**	-0.0545**
1996-1998	9	0.0160*	0.0752*	0.1427*	0.1543*	9	-0.0004	0.0143**	0.0264**	0.0262***
1999-2001	3	0.0145*	0.0639*	0.1213*	0.1435*	3	0.0009	0.0061	0.0033	-0.0078
2002-2004	0	0.0013	0.0188	0.0466	0.0705	0	-0.0026**	-0.0039**	-0.005***	-0.0082
2005-2007	6	0.0036*	0.0224*	0.0570*	0.0766*	6	0.0010	0.0014	0.0033	0.0010
2008-2010	0	0.0017	0.0194*	0.0611*	0.0884*	0	-0.0019	-0.0061**	-0.0054**	0.0002
2011-2013	0	-0.003	-0.0055	-0.0089	-0.0109	0	-0.0027	-0.0040	-0.0057	-0.0049
2014-2016	8	0.0206*	0.0651*	0.1506*	0.1964*	8	-0.0013	0.0017	-0.0008	-0.0041
2017-2019	7	0.0048*	0.0257*	0.0699*	0.0934*	7	-0.0005	-0.0036	-0.0030	-0.0019

2020-2022	1	0.0018	0.0173*	0.0414*	0.0810*	1	-0.0028	-0.0064**	-0.0119**	-0.0143
Panel C: Brazil (IBOVESPA)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	3	0.0208*	0.0219*	0.0181*	0.0119*	3	-0.0008	0.0032**	0.0202*	0.0242*
1990-1992	0	0.0043	0.0112*	-0.0015	-0.001	1	0.0057	0.0142	0.0032	0.0294
1993-1995	9	0.0049*	0.0255*	0.0656*	0.1185*	9	0.0001	0.0003	-0.0009	0.0002
1996-1998	9	0.0219*	0.0869*	0.1874*	0.2194*	9	0.0011	-0.0010	0.0005	0.0022
1999-2001	5	0.0047*	0.0155*	0.0463*	0.0774*	5	0.000295	-0.0005	0.0011	0.0006
2002-2004	0	0.0004	0.0046	0.0215*	0.0564*	0	-0.0011	-0.0037***	-0.0028	-0.0014
2005-2007	0	-0.0008	0.0038	0.0262*	0.0454*	0	-0.0017	-0.0009	0.0031	0.0029
2008-2010	3	0.0120*	0.0582*	0.1414*	0.2086*	3	-0.0007	-0.0005	0.0031	0.0053
2011-2013	0	0.0004	0.0088*	0.0246*	0.0542*	0	-0.0010***	0.0013**	0.0078**	0.0223**
2014-2016	0	0.0005	0.0074	0.0262	0.0567	1	-0.0017	-0.0020	-0.0027	0.0011
2017-2019	7	0.0016	0.0047	0.0188	0.0335	7	-0.0004	-0.0025	0.0024	0.0066
2020-2022	8	0.0052*	0.0292*	0.0868*	0.1561*	8	-0.0013***	-0.0026**	-0.0042**	-0.0093**
Panel D: South Africa (JALSH)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	7	0.0079*	0.017*	0.087*	0.144*	7	-0.0004	0.0004	0.0018	0.0025
1993-1995	1	0.0080*	0.0396*	0.0959*	0.1441*	1	-0.0005	0.0005	0.0018	0.0025
1996-1998	4	0.0076*	0.0247*	0.0459*	0.0907*	4	0.0062**	0.0037	0.0025**	0.0184
1999-2001	2	0.0242*	0.1013*	0.1988*	0.2246*	2	-0.0020	-0.0029	-0.0061	-0.0096
2002-2004	3	0.0008	0.0071	0.0197*	0.0416*	3	-0.0015	-0.0015	0.0006	0.0034
2005-2007	0	0.0090*	0.0287*	0.0743*	0.1258*	0	-0.0001	-0.0002	-0.0011	-0.0035
2008-2010	3	0.0165*	0.0551*	0.1289*	0.1843*	3	-0.0017**	-0.0016**	-0.0013	-0.0022
2011-2013	0	0.0043*	0.0191*	0.0396*	0.0732*	0	-0.0002	0.0015	0.0016	0.0003
2014-2016	2	0.0043*	0.0244*	0.0568*	0.0894*	2	0.0002	0.0020**	0.0029**	-0.0020
2017-2019	0	0.0027*	0.0056	0.0331	0.0584	0	-0.0008	-0.0021	0.0030	0.0087
2020-2022	8	0.0097*	0.0307*	0.0626*	0.1008	8	-0.0011	-0.0002	-0.0013	-0.0035
Panel E: Russia (MOEX)										

	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	14	0.0241*	0.1015*	0.2057*	0.2282*	14	-0.0011	-0.0002	0.002289	0.001471
1996-1998	2	0.0267*	0.0737*	0.1253*	0.1434*	2	0.0065**	0.0163**	0.0246**	0.0141**
1999-2001	1	0.0063*	0.0253*	0.0551*	0.0848*	1	-0.0003	0.0015	0.0005	-0.0022
2002-2004	3	0.0025**	0.0156*	0.0480*	0.0889**	3	-0.0017***	-0.0028***	-0.0006	0.0059
2005-2007	1	0.0108*	0.0366*	0.0831*	0.1379*	1	-0.0006	-0.0005	0.001422	0.000707
2008-2010	0	0.0151**	0.0749*	0.1461*	0.1747*	0	-0.0031	-0.0031**	-0.0066**	-0.0073
2011-2013	0	0.0055***	0.0151*	0.0395*	0.0825*	0	-0.0028	-0.0021	-0.0042	-0.0013
2014-2016	1	0.0042*	0.0215*	0.0561*	0.0908*	1	0.0015	0.0022	0.0066	0.0108
2017-2019	0	0.0005	0.0111*	0.0286*	0.0490*	0	-0.0028**	0.0008	0.0063	0.0083
2020-2022	1	0.0227*	0.0964*	0.1773*	0.1748*	1	-0.0035***	-0.0053	-0.0063**	-0.0021

Source: *Author's computation Using EViews*

Note(s): The table presents the BDS test statistic values for the AR filter and the standardized AR-GARCH filter. The "M" column represents the embedding dimension, which is the number of consecutive data points used to reconstruct the phase space of the time series. The "e" column represents the value of the standard deviation of the sample, which is used as the scaling factor for the embedding dimension. *, **, *** indicates significant at 1%, 5% and 10% level respectively.

3.5.2. BDS test result for G5 markets

Table 3.10 reports the BDS test for AR-filtered and AR-GARCH-filtered returns over the full sample and subperiods for G5 markets. Panel A of Table 3.10 reports the findings for the CAC 40 market, considering both AR-filtered and AR-GARCH-filtered returns over the full sample and subperiods. The CAC 40 stock returns exhibit nonlinear dependence for the whole sample period and most subperiods, except 1993-1995, 2002-2004 and 2014-2016, implying nonlinearity predictability in the CAC 40 market. Applying AR-GARCH filtering substantially reduced the magnitude of the BDS test statistics. However, certain periods like 1999-2001, 2002-2004, 2008-2010, 2011-2013, and 2014-2016 still rejected the null hypothesis of independent and identically distributed (i.i.d) returns, indicating residual nonlinear dependence after accounting for heteroscedasticity.

Panel B reports the AR-filtered and AR-GARCH filtered return over the full sample and subsample for the DAX 30 index return. The DAX 30 index returns exhibit nonlinear dependence for the whole sample period. The estimated output of the AR filtered shows the subsample period provides nonlinearity predictability in the stock return except for the period of 1993-1995 and 2008-2010 subsample. The AR-GARCH filtering rejects the null hypothesis of i.i.d returns in the full sample and the subsample periods during 199-1992, 1996-1998, 1999-2001, 2004-2006, 2008-2010 and 2014-2016 and 2017-19, indicating residual nonlinear dependence in the returns. The DAX 30 has undergone a period of independence and dependence over the sample studies indicating the evidence of AMH and type 4 classification and the null hypothesis of H_{03a} is rejected.

Panel C of Table 3.10 reports the AR-filtered and AR-GARCH filtered returns over the full sample and subsample for FTSE 100. The AR filter returns exhibit nonlinear dependence for the whole sample period. In the AR filtered, the subsample period provides nonlinearity predictability in the stock return except from 1999 to 2001, 2002 to 2004, and 2020 to 2022 subsamples. The AR-GARCH filtering rejects the null hypothesis of i.i.d returns, rejected during the period of 1999-2001, 2002-2004, 2008-2010, 2014-2019 and 2020-2020, indicating residual nonlinear dependence in the returns. The FTSE 100 revealed alternating periods of independence and dependence over time, indicating that market efficiency varies across different periods. This nonlinear, time-varying pattern led to the rejection of null hypothesis H_{03a}, which assumed the market has switched to efficiency and can be described nonlinear time-varying pattern.

Panel D of Table 3.10 reports the AR-filtered and AR-GARCH filtered return over the full sample and subsample for Nikkei 225. The AR filter returns exhibit nonlinear dependence for the whole sample period. The AR filtered provides nonlinearity predictability in the stock market except for the period of 1999-2001, 2022 and 2020-2022. The AR-GARCH filtering reject the null hypothesis of i.i.d returns, rejected during 1996-1998, 2008-2010, and 2014-2016, 2017-2019 and 2020-2022 subsample, indicating residual nonlinear dependence in the returns. The Nikkei 225 has undergone a period of independence overtime and return dependence was found in certain periods this indicates the market is switched to inefficient and can be described as type 3 classification and AMH resulting in the rejection of H_{03a}.

Panel E of Table 3.10 reports the AR filtered and AR-GARCH filtered return over the full sample and subsample for S&P 500. The AR filter returns exhibit nonlinear dependence for the whole sample period. The subsample period provides nonlinearity predictability in the stock return was failed to rejected during 1993-1995,1999-2001, and 2008-2010 subsample periods. The AR-GARCH filtering reject the null hypothesis of i.i.d returns, rejected during the whole sample and 2002-2004, 2008-2010, 2011-2013, 2017-2019 and 2020-2022 subsample, indicating residual nonlinear dependence in the returns. The S&P 500 has undergone a period independence overtime and dependence was found to be appear in certain period this indicate the market are switch to inefficient and can be describe as type 4 classification.

Table 3.10: BDS test result on AR filtered and AR-GARCH filtered stock return for G5 Countries

	AR filtered on stock return					Residual fitted of the GARCH model				
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Panel A: France (CAC 40)										
Full Sample	6	0.0071*	0.0357*	0.0894*	0.1395*	6	-0.0008**	-0.0003	0.0014	-0.0009
1990-1992	5	0.0046*	0.0204*	0.0632*	0.1101*	5	-0.0012	-0.0045	-0.0011	-0.0028
1993-1995	0	-0.0003	-0.0020	-0.0050	-0.0119	0	0.0004	-0.0015	-0.0017	-0.0044
1996-1998	7	0.0042**	0.0190*	0.0619*	0.1178*	7	0.0005	-0.0014	-0.0012	0.0009
1999-2001	2	0.0019**	0.0065**	0.0210*	0.0449	2	-0.0004	-0.0026***	-0.0046	-0.0089
2002-2004	6	0.0161	0.0624	0.1539	0.2202	6	-0.0027**	-0.0028**	-0.0062**	-0.0092**
2005-2007	1	0.0064*	0.0207*	0.0584*	0.1048*	1	-0.0003	0.0014	0.0023	0.0042
2008-2010	5	0.0021	0.0252*	0.0752*	0.1552*	5	-0.0055**	-0.0056**	-0.0101***	-0.0114**
2011-2013	5	0.0073*	0.0312*	0.0771*	0.1162*	5	-0.0020	0.0046	0.0091***	0.0056
2014-2016	5	0.0145*	0.0341	0.0684	0.0947	5	0.0036**	0.0055**	0.0068**	-0.0009
2017-2019	0	0.0063*	0.0400*	0.0564*	0.0719*	0	-0.0003	0.003055	0.0058	-0.0024
2020-2022	8	0.0120*	0.0420*	0.0872*	0.1399*	8	0.0012	0.0018	0.0011	-0.0044
Panel B: Germany (DAX 30)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	6	0.0091*	0.0446*	0.1077*	0.1573*	6	-0.0011**	-0.0022**	0.0025***	0.0029
1990-1992	1	0.0075*	0.0385*	0.0911*	0.1245*	1	-0.0012	0.0025	0.0148**	0.0218**
1993-1995	0	0.0003	0.0063	0.0176**	0.0410*	0	-0.0024	-0.0026	-0.0033	-0.0053
1996-1998	7	0.0140*	0.0527*	0.1238*	0.1642*	7	-0.0031**	-0.0030	-0.0014	-0.0008
1999-2001	0	0.0058*	0.0146*	0.0352*	0.0711*	0	-0.0009**	-0.0016**	-0.0037	-0.0082

2002-2004	1	0.0087*	0.0596*	0.1472*	0.2073*	1	-0.0027**	-0.0047**	-0.0080***	-0.006***
2005-2007	0	0.0098*	0.0223*	0.0479*	0.0784*	1	0.0031	0.0045	0.0059	0.0029
2008-2010	4	0.0040	0.0278*	0.0908*	0.0017*	4	-0.0039**	-0.0050**	-0.0094***	-0.0088**
2011-2013	5	0.0088*	0.0410*	0.0928*	0.1459*	5	-0.0008	0.0047	0.0054	-0.0027
2014-2016	5	0.0056*	0.0228*	0.0687*	0.0780*	5	0.0032**	0.0029***	0.0068	0.0058**
2017-2019	0	0.0079*	0.0197*	0.0338*	0.0468*	0	0.0016	0.0062***	0.0072	0.0015
2020-2022	8	0.0143*	0.0413*	0.0836*	0.1164*	8	0.0013	0.0005	0.0008	-0.0038
Panel D: United Kingdom (FTSE 100)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	17	0.0087*	0.0043*	0.1207*	0.1597*	17	-0.0007	0.0003	0.0027**	0.0027
1990-1992	7	0.0007	0.0048	0.0167**	0.0471*	7	-0.0019	-0.0052	-0.0050	-0.0054
1993-1995	0	0.0002	0.0033	0.0074	0.0075	0	-0.0033**	-0.0028**	-0.0006	-0.0054
1996-1998	9	0.0136*	0.0354*	0.0902*	0.1410*	9	0.0012**	0.0004**	0.0010**	0.0073**
1999-2001	2	0.0020	0.0068**	0.0287*	0.0623*	2	-0.0032	-0.0032	0.0012	0.0046
2002-2004	7	0.0145*	0.0731*	0.1716*	0.2399*	7	-0.0005	-0.0003	0.0031	0.0078
2005-2007	1	0.0093*	0.0469*	0.1176*	0.1832*	1	-0.0007	0.0055	0.0012	0.0004
2008-2010	9	0.0086**	0.0348*	0.1058	0.1797	9	-0.0055**	-0.0081**	0.0005**	-0.0072**
2011-2013	0	0.0089**	0.0279*	0.0979*	0.1160*	0	-0.0006	0.003116	0.004976	-0.0011
2014-2016	5	0.0176*	0.0439*	0.0903	0.1416	5	0.0019	0.0026	0.0044	0.0039
2017-2019	0	0.0075*	0.0142*	0.0313*	0.0508*	0	0.0024	-0.0005	-0.0023	-0.0039
2020-2022	8	0.0161*	0.0474*	0.1005*	0.1400*	8	0.0022**	0.0028**	0.0013**	0.0044
Panel D: Japan (Nikkei 225)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	2	0.0061*	0.0303*	0.0677*	0.1177*	2	-0.0009**	-0.0004	0.000358	-0.0008
1990-1992	2	0.0144*	0.0351*	0.0885*	0.1202*	2	-0.0002	-0.0025	0.00223	0.0031
1993-1995	0	0.0093*	0.0229*	0.0551*	0.0727*	0	0.0007	0.0007	0.0048	0.0062
1996-1998	4	0.0093*	0.0244*	0.0593*	0.1051*	4	-0.0017	-0.0013	-0.0020	-0.0008

1999-2001	1	-0.0010	0.0046	0.0012	0.0089	1	-0.0033**	-0.0060**	-0.0024	-0.0055
2002-2004	0	-0.0018	0.0018	0.0160*	0.0426	0	-0.0041**	-0.0057**	-0.0058	-0.0070
2005-2007	0	0.0061**	0.0200**	0.0516*	0.0818*	0	-0.0030	-0.0033	-0.0010	-0.0062
2008-2010	1	0.0101*	0.0357*	0.1159*	0.1975*	1	-0.0024**	-0.0042**	-0.0078**	0.003513
2011-2013	9	0.0029***	0.0124*	0.0346*	0.0758*	9	-0.0027	-0.0017	-0.0045	-0.0052
2014-2016	1	0.0132*	0.0053*	0.0948*	0.1120*	1	0.0008	0.0022*	0.0069**	0.0002
2017-2019	1	0.0076*	0.0277*	0.0436*	0.0647*	1	0.0040**	0.0123**	0.0127***	0.0029
2020-2022	3	0.0117	0.0253	0.0558	0.0906	3	0.0069**	0.0141*	0.0282*	0.0517*
Panel E: U.S (S&P 500)										
	AR Model	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**	**AR-GARCR**	**M=2, e=0.5**	**M=4, e=1**	**M=8, e=1.5**	**m=10, e=2**
Full Sample	18	0.0169*	0.0565*	0.1089*	0.1748*	18	0.0050*	0.0297*	0.0776*	0.1122*
1990-1992	2	0.0037	0.0112*	0.0336*	0.0655*	2	-0.0003	0.0010	0.0053	0.0136
1993-1995	0	0.0005	-0.0006	0.0088	0.0189	0	-0.0005	-0.0053	-0.0046	-0.0007
1996-1998	0	0.0056**	0.0195*	0.0568*	0.0910**	0	-0.0008	-0.0036	-0.0028	-0.0035
1999-2001	5	-0.0011	0.0042	0.0229**	0.0508	5	-0.0038	-0.0022	0.0006	0.0002
2002-2004	0	0.0094*	0.0312*	0.0981*	0.1637*	0	-0.0027**	-0.0049*	-0.0069***	-0.0038**
2005-2007	1	0.00266	0.0050	0.0556**	0.0998**	1	-0.0028	-0.0035	-0.0008	0.0014
2008-2010	3	0.0152	0.0551	0.1314	0.2171	3	-0.0047**	-0.0062	-0.0111**	-0.013***
2011-2013	5	0.0114*	0.0410*	0.1024*	0.1640*	5	-0.004**	-0.0006	-0.0066**	-0.0048**
2014-2016	0	0.0170*	0.0501*	0.0961*	0.1309*	0	0.0015	0.0017**	0.0041	0.0072
2017-2019	8	0.0179*	0.0647*	0.1540*	0.1946*	8	-0.0038**	- 0.0060***	0.0069**	0.0079
2020-2022	9	0.0173*	0.0586*	0.1109*	0.1511*	9	0.0002	0.0001	0.0035**	0.0055

Source: *Author's computation Using EViews*

Note(s): The table presents the BDS test statistic values for the AR filter and the standardized AR-GARCH filter. The "M" column represents the embedding dimension, which is the number of consecutive data points used to reconstruct the phase space of the time series. The "e" column represents the value of the standard deviation of the sample, which is used as the scaling factor for the embedding dimension. *, **, *** indicates significant at 1%, 5% and 10% level respectively

3.5. Conclusion

The efficient market hypothesis (EMH) was widely accepted in the financial literature. The EMH gained widespread acceptance in the mid-1990s, with the majority of studies supporting the notion of efficient markets. However, the issue of market efficiency was a longstanding debate among researchers, as numerous market inefficiencies have been observed. This chapter examines whether stock returns exhibit time dependence or independence. By employing various linear and nonlinear statistical tests, this chapter investigates the presence of time dependencies or predictable patterns in stock returns over different time periods. The linear tests aim to detect linear dependencies, while the nonlinear tests are designed to capture potential nonlinear relationships or complex dynamics that may exist in the data. This chapter contributes to the understanding of how the independence of stock returns has evolved over time, potentially shedding light on the dynamics of market efficiency and challenging or supporting the EMH in various market contexts.

The Key Conclusion are:

1. **Linear Autocorrelation test:** The linear autocorrelation test suggests that the BSE, SSE, IBOVESPA, and JALSH markets displayed adaptive behaviour, with periods of efficiency and inefficiency, the MOEX market exhibited characteristics consistent with the EMH, suggesting it can be considered an independent of stock returns based on the linear autocorrelation test results for BRICS countries. The results for the G5 countries revealed stock indices exhibit behaviour consistent with the AMH, where market efficiency is a dynamic process, with stock returns alternating between periods of predictability (inefficiency) and unpredictability (efficiency) overtime. Based on these findings, we reject the null hypotheses H_{01a} and H_{03a}.
2. **Linear Variance ratio test:** The variance ratio tests revealed the BRICS markets displayed a mix of AMH and EMH traits. The G5 stock markets exhibited behaviour consistent with the AMH, with shifts between efficiency and inefficiency over time. These results provide sufficient statistical evidence to reject null hypotheses H_{01a} and H_{03a}, supporting BRICS and G5 market exhibit significant linear time-varying patterns.

3. **Nonlinear battery test:** After filtering the returns through an autoregressive (AR) model to remove linear correlations, all markets under study provided evidence of significant nonlinear dependence in stock returns using the McLeod-Li Engle LM and BDS test. The result failed to reject the null hypotheses H_{02a} and H_{04a}.
4. **Nonlinear AR-GARCH BDS test:** The study employed an AR-GARCH filter to address the issue of heteroscedasticity and residual nonlinearity persisting even after AR filtering. The findings rejected the null hypotheses H_{05a} in both the BRICS and G5 markets and aligns with the Adaptive Market behaviour, characterised by alternating periods of market efficiency and inefficiency.

The summary of Linear test results in Table 3.11 and Table 3.12 suggest that the Adaptive Market Hypothesis (AMH) is more applicable in developed countries (G5 markets) compared to emerging countries (BRICS markets). The result of the linear test from the G5 countries indicates that the adaptive nature of behaviours is the likely outcome. According to the Efficient Market Hypothesis (EMH), stock returns should exhibit no dependence, or if any dependence exists, it should dissipate rapidly as investors exploit such opportunities. The findings reveal that stock return dependencies were prevalent in most cases among the BRICS countries, except for the Moscow Exchange (MOEX) and G5 countries. The dependence of stock returns manifested over the sample period and subsequently reverted to independence throughout the remainder of the sample with time varying or episodic dependence in stock returns.

To obtain robust results and determine the presence of any significant time dependence in stock returns, a nonlinear dependence test was conducted. In this test, an autoregressive (AR) filter was applied to the return series to remove any linear correlation. This step was taken to ensure that the subsequent analysis focused solely on nonlinear dependencies using a battery of statistical test including Engle- LM, McLeod-Li and BDS test resulting in providing a more nuanced understanding of the underlying market dynamics. The result indicates that dependencies in the stock return are found in both BRICS and G5 countries. The AR filter might successfully eliminate linear correlation but left behind some heteroscedasticity in the returns (Lim & Hooy, 2012; Urquhart, 2013). To address this concern, the AR-GARCH model was employed to remove the heteroscedasticity properties in the return series. The result on AR-GARCH BDS test suggest that stock market under investigation exhibits an adaptive nature (AMH). This means that the characteristics of stock returns do not remain statics, rather fluctuate overtime and display a period of both dependence and independence. In summary, the evidence presented in this chapter appears to be in supportive of the AMH and the dynamic nature of stock market return dependencies.

Table. 3.11: Summary and classification of test result for BRICS countries

	Autocorrelation	VR test	Joint VR test	McLeod-Li	Engle LM	AR-BDS Test	AR-GARCH BDS test
	Panel A: India (BSE Sensex)						
Full Sample	D	D	D	D	D	D	D
1990-1992	I	I	I	D	D	D	I
1993-1995	D	D	D	D	D	D	I
1996-1998	D	D	D	D	D	D	I
1999-2001	I	I	D	D	D	D	I
2002-2004	D	I	I	D	D	D	I
2005-2007	I	I	D	D	D	D	D
2008-2010	I	I	I	D	D	D	D
2011-2013	I	D	D	D	D	I	D
2014-2016	I	D	D	D	D	I	D
2017-2019	D	I	I	D	D	D	I
2020-2022	I	D	D	D	D	D	I
Classification	AMH	AMH	AMH	Inefficient	Inefficient	Inefficient	Switch Efficient
Panel B: China (SSE Composite)							
Full Sample	D	D	D	D	D	D	D
1990-1992	D	D	D	I	I	I	I
1993-1995	D	I	I	D	D	D	D
1996-1998	D	I	I	D	D	D	D
1999-2001	D	D	D	D	D	D	I
2002-2004	I	I	I	D	D	D	D
2005-2007	I	D	D	D	D	D	I
2008-2010	D	I	I	D	D	D	D
2011-2013	I	I	I	D	I	I	I
2014-2016	I	I	I	D	D	D	I
2017-2019	I	I	I	D	D	D	I
2020-2022	D	I	I	D	D	D	D
Classification	AMH	AMH	Switch Efficient	Inefficient	Inefficient	Inefficient	AMH

Panel C: Brazil (IBOVESPA)							
Full Sample	D	I	D	I	D	D	D
1990-1992	I	I	I	I	D	I	I
1993-1995	D	D	D	D	D	D	I
1996-1998	D	I	I	D	D	D	I
1999-2001	D	I	I	D	D	D	I
2002-2004	I	I	I	D	I	I	D
2005-2007	I	D	D	D	D	I	I
2008-2010	D	I	I	D	I	D	I
2011-2013	I	I	I	D	I	I	D
2014-2016	I	D	I	D	D	I	I
2017-2019	D	D	D	D	D	I	I
2020-2022	D	I	D	D	D	D	D
Classification	AMH	AMH	AMH	Inefficient	Inefficient	AMH	AMH
Panel D: South Africa (JALSH)							
Full Sample	D	D	D	D	D	D	I
1993-1995	D	I	I	D	D	D	I
1996-1998	D	D	D	D	D	D	D
1999-2001	I	D	D	D	D	D	I
2002-2004	D	D	D	D	D	I	I
2005-2007	I	I	I	D	D	D	I
2008-2010	I	I	I	D	D	D	D
2011-2013	I	I	I	D	D	D	I
2014-2016	I	D	I	D	D	D	D
2017-2019	I	I	I	D	D	I	I
2020-2022	D	I	D	D	D	D	I
Classification	AMH	AMH	AMH	Inefficient	Inefficient	Inefficient	AMH
Panel E: Russia (MOEX)							
Full Sample	D	D	D	D	D	D	I
1996-1998	I	D	D	D	D	D	D
1999-2001	I	D	D	D	D	D	I
2002-2004	D	I	I	D	D	D	D
2005-2007	I	I	I	D	D	D	I
2008-2010	D	I	I	D	D	D	D
2011-2013	I	D	D	D	D	D	I
2014-2016	I	I	I	D	D	D	I
2017-2019	I	D	D	D	I	D	I
2020-2022	I	I	I	D	I	D	D
Classification	EMH	AMH	AMH	Inefficient	Inefficient	Inefficient	AMH

Source: *Author's computation*

Note(s): "I" assumes stock returns are random and independent, while "D" assumes that stock prices are driven or affected by past returns, implying a certain level of predictability or momentum in price movements.

Table. 3.12: Summary and classification of test result for G5 countries

	Autocorrelation	VR test	Joint VR test	McLeod-Li	Engle LM	AR-BDS Test	AR-GARCH BDS test
	Panel A: France (CAC 40)						
Full Sample	D	D	D	D	D	D	D
1990-1992	D	I	I	D	D	D	I
1993-1995	I	D	D	D	I	I	I
1996-1998	D	I	I	D	D	D	I
1999-2001	I	I	I	D	D	D	D
2002-2004	D	D	D	D	D	I	D
2005-2007	I	D	D	D	D	D	I
2008-2010	D	D	D	D	D	I	D
2011-2013	I	D	D	D	D	D	I
2014-2016	D	I	I	D	D	I	D
2017-2019	I	I	I	D	D	D	I
2020-2022	I	I	I	D	D	D	I
Classification	AMH	AMH	Switch Efficient	Inefficient	Inefficient	AMH	AMH
Panel B: Germany (DAX 30)							
Full Sample	D	D	D	D	D	D	D
1990-1992	I	I	I	D	D	D	D
1993-1995	I	I	I	D	D	I	I
1996-1998	D	I	I	D	D	D	I
1999-2001	I	I	I	D	D	D	D
2002-2004	D	D	I	D	D	D	D
2005-2007	I	I	D	D	D	D	I
2008-2010	D	I	I	D	D	D	D
2011-2013	I	I	D	D	D	D	I
2014-2016	D	I	I	D	D	D	D
2017-2019	I	I	I	D	D	D	I
2020-2022	D	D	I	D	D	D	I
Classification	AMH	EMH	EMH	Inefficient	Inefficient	Inefficient	AMH
Panel C: United Kingdom (FTSE 100)							
Full Sample	D	D	D	D	D	D	D
1990-1992	D	I	D	D	D	D	I
1993-1995	I	I	I	D	D	I	I
1996-1998	D	D	D	D	D	D	I
1999-2001	D	I	D	D	D	D	I
2002-2004	D	I	I	D	D	D	D
2005-2007	I	D	I	D	D	D	I
2008-2010	D	D	D	D	D	I	I
2011-2013	I	I	I	D	D	D	D

2014-2016	D	I	I	D	D	I	I
2017-2019	I	I	I	D	D	D	I
2020-2022	I	D	D	D	D	D	D
Classification	AMH	AMH	AMH	Inefficient	Inefficient	AMH	AMH
Panel D: Japan (Nikkei 225)							
Full Sample	I	D	D	D	D	D	D
1990-1992	D	I	I	D	D	D	I
1993-1995	I	I	D	D	D	D	I
1996-1998	D	D	D	D	D	D	I
1999-2001	I	I	I	D	D	I	D
2002-2004	I	I	I	D	D	I	D
2005-2007	I	D	I	D	D	D	I
2008-2010	I	I	I	D	D	D	D
2011-2013	D	I	I	D	D	D	I
2014-2016	I	I	I	D	D	D	I
2017-2019	I	D	D	D	D	D	D
2020-2022	D	I	D	D	D	I	D
Classification	AMH	AMH	Switch Efficient	Inefficient	Inefficient	Inefficient	AMH
Panel E: U.S (S&P 500)							
Full Sample	D	D	D	D	D	D	D
1990-1992	I	I	I	D	D	D	I
1993-1995	D	I	D	D	D	I	I
1996-1998	I	I	D	D	D	D	I
1999-2001	D	I	I	D	D	D	I
2002-2004	I	I	D	D	D	D	D
2005-2007	I	D	D	D	D	D	I
2008-2010	D	D	D	D	D	I	D
2011-2013	D	I	I	D	D	D	D
2014-2016	I	I	D	D	D	D	I
2017-2019	D	I	I	D	D	D	D
2020-2022	D	D	D	D	D	D	I
Classification	AMH	AMH	AMH	Inefficient	Inefficient	Inefficient	AMH

Source: *Author's computation*
Note(s): "I" assumes stock returns are random and independent, while "D" assumes that stock prices are driven or affected by past returns, implying a certain level of predictability or momentum in price movements.

CHAPTER 4: The Behaviour of Calendar anomalies and its market conditions

4.1. Introduction

The fundamental theoretical concept from the EMH states that financial markets are efficient, and asset prices reflect all available information at any given time. It assumes that all market actors are fully rational and have access to complete information, making it impossible for investors to outperform the market or earn excess returns through arbitrage opportunities. The EMH holds that, assets are always properly valued, and investors need to take on additional risk to earn higher returns (Fama, 1970). The constraint and flawed efficient theory were challenged with the existence of stock market anomalies when documented with theoretical and empirical evidence. For example, the day-of-the-week (Cross, 1973), the weekend effect (French, 1980), the month-of-the-year effect (Reignganum,1983; Rozeff & Kinney, 1976), and the turn-of-the-month effect (Ariel, 1987) have been found to have a significant predictive ability. These anomalies suggest that asset prices do not always reflect all available information and that investors may be able to earn abnormal returns by exploiting certain calendar-based trading strategies. Calendar anomalies are recurring patterns in stock market returns associated with specific periods. They form part of the broader market environment, influencing investor behaviour and potentially affecting asset prices. This chapter focuses on calendar anomalies and explore the dynamic pattern of calendar anomalies and identify which trading strategies, outperform under different market conditions.

In this chapter, the study was conducted and analysed by categorizing the objective into three main areas as follows:

- To examine the presence of calendar anomalies, specifically the day-of-the-week effect, the month-of-the-year effect, and the turn-of-the-month effect, on stock returns and volatility, the nonlinear symmetric GARCH (1,1) model and the nonlinear asymmetric EGARCH (1,1) model were employed.
- The adaptive calendar effect was investigated using the GARCH (1,1) model for a fixed window of 3 years. This analysis aimed to understand the behaviour of the market environment over time and their potential evolution.

- To evaluate whether investors can exploit calendar anomalies for profit, the returns of a simple buy-and-hold (BH) strategy was compared to those of an implied trading strategy (ITS) that benefit from calendar anomalies.

The chapter is organised in the following manner. Section 4.2 describes the literature review, Section 4.3 layout the methodology, Section 4.4 provides the empirical result of the calendar anomalies, Section 4.5 provides a graphical representation of adaptive calendar anomalies, and Section 4.6 provides possible excess return from trading strategy.

4.2. Review of related studies

4.2.1. Day-of-the-week effect

Numerous studies were conducted on the variation in return depending on the day-of-the-week. Cross (1973) was undoubtedly among the first to take into account the fact that Monday effect had higher stock returns than other days. The literature mainly focuses on the price difference between the beginning (Monday) and end (Friday) of the week. In particular, stock prices often being higher on Fridays than any other day-of-the-week and lower on Mondays than every other day-of-the-week. Previous studies (Cross, 1973; Fama 1980; Jaffe & Westerfield,1985) were crucial in identifying and documenting the day-of-the-week effect, notably the Monday effect and the weekend effect, in stock market returns. Their findings challenged the efficient market hypothesis by revealing systematic patterns in stock price movements based on the day-of-the-week. The day-of-the-week effect was first examined by Cross (1973), which is considered one of the earliest studies. The study analysed stock market data from the period of 1953 to 1970 for the Standard & Poor's Composite Index. The methodology involved calculating the average daily returns for each day-of-the-week and comparing them to identify any significant differences. Cross (1973) observed that Monday returns were significantly lower compared to other days of the week. This phenomenon became known as the "Monday effect" or the "weekend effect," suggesting that stock prices tend to decline on Mondays, potentially due to the accumulation of negative news over the weekend or investors' psychological factors.

Fama (1980) extended the research on the day-of-the-week effect by examining data from various stock market indices, including the S&P 500, the Dow Jones Industrial Average, and the NYSE Composite Index. The study covered a longer time period, spanning from 1962 to 1978. Fama's (1980) findings corroborated the existence of the Monday effect, as observed in Cross's (1973) study. Specifically, Fama found that Monday returns were significantly lower than returns on other days of the week, particularly when compared to Friday returns. Jaffe and Westerfield (1985) further investigated the day-of-the-week effect by analysing data from the S&P 500 index and the equally weighted NYSE index over the period of 1962 to 1983. Their study not only confirmed the presence of the Monday effect but also identified another anomaly known as the "weekend effect." Further, Kleim and Stambaugh (1984) carried out a study in the Singapore stock market and discovered the weekend effect. The result is consistent with Wong and Ho (1986) analysis of Chinese all share and sectoral index. Cheung and Hu (1997) examining the day-of-the-week effect of Asian stocks found Monday return is lowest in five trading days in Malaysia and Tuesday retains the lowest stock return in six trading days in Japan, Korea and Taiwan. Overall, the returns on the last day-of-the-week gain the highest. Consistent with Cheung and Hu (1997) finding Wong et al. (1992) also found the day-of-the-week effect in developing countries.

Recent studies on the day-of-the-week effect have continued to examine this anomaly across different markets and time periods. Zhang et al. (2017) investigated the day-of-the-week effect on stock returns in 25 countries using rolling sample windows and GARCH models. The results provide robust evidence that day-of-the-week anomalies persist in both emerging and developed equity markets, with different weekdays exhibiting prominent effects in different countries. The authors propose a metric to quantify the significance of these calendar effects, which can aid investors in exploiting such anomalies for higher returns. Further, Çinko et al. (2015) come with conclusive research as there is no clear-cut evidence of this anomalies in the emerging and developed market. In their study, they focussed on 33 stock indices of developed markets from 1999-2013. They documented the "Monday effect" (negative returns) and the "Friday effect" (positive returns), as well as significant returns on certain days

(Wednesday and Thursday), they observed no consistent pattern across all the indices, suggesting that the day-of-the-week effect is not a universal phenomenon in these developed stock markets during the analysed period. Chatzitzisi et al. (2019) examined the day-of-the-week effect using S&P 500 sectoral data from 1989 to 2017. To analyse the daily returns and volatility patterns, the study employed various statistical tests, such as GARCH models and regression analysis. The presence of significant evidence of day-of-the-week effect was the major finding of the study. Additionally, the study found evidence of a seasonality in the market experiencing a period of inefficient market and efficient in the market. Agarwal and Jha (2023) studied the day-of-the-week effect in the Indian stock market using GARCH (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models. The study which covered a 28-year period from 3 July 1990 to 31 March 2022 analysed the stock returns and volatility in the NSE-Nifty market. The day-of-the-week effect on returns and volatility was observed using the GARCH models. All weekdays showed positive and significant returns. Additionally, the asymmetric GARCH models revealed significant asymmetric (leverage) effects in daily stock returns. GKillas et al. (2021) also found significant day-of-the-week effect in the international market of three different economic regions comprising 17 stock markets across Asian, American and European markets.

Different studies have also provided contradicting results regarding the effect of day-of-the-week effect across various countries. Gibbons (1981) discovered that even though there were significant day-of-the-week effects, they were not concentrated on Monday. Basher and Sadorsky (2006) conducted a study on emerging stock markets, claiming that most emerging markets do not display significant day-of-the-week patterns. Stavarek and Heryán (2012) estimated the DOW effect in the stock markets of Central European over the period 2006–2012 using modified GARCH-M (1,1). They found an anomaly in the stock market immune to DOW Effect in central European. Moreover, the financial crisis did not seem to increase the incidence of day-of-the-week effects. The study also claimed that no significant DOW or difference in the level of returns across the days of the week in the Indonesian (LQ45), Japanese (Nikkei), and American (DJIA) markets were observed pre Covid-19, during Covid-19 and after the Covid-19 pandemic (Komariah & Ramadhan, 2022). Kamath and

Chusanachoti (2002) examined the day-of-the-week effect in the Korean stock market using data from 1980 to 1997. In the study, the daily returns were analysed using both parametric and non-parametric tests. The results revealed a significant negative Monday effect, however, after 1990 the day-of-the-week disappeared completely. Olson et al. (2015) conducted a comprehensive study on the day-of-the-week effect in the U.S. stock market using data from 1963 to 2013. To analyse the returns and volatility patterns, the study employed various statistical techniques, including GARCH models and regression analysis. The major finding was the persistence of the Monday effect, with significantly lower returns on Mondays compared to other weekdays. However, the study also noted that the magnitude of the Monday effect had diminished over time. Chia (2014) investigated the day-of-the-week effect in the New Zealand and Australia using data from 2002 to 2014. The study employed various statistical tests, including the TAR-GARCH model, to analyse the returns and volatility patterns across different days of the week. The major finding was that the day-of-the-week effect is disappearing for both the market. Those finding is consistent with earlier finding in other studies in Korean stock market (Kamath & Chusanachoti, 2002) and United Kingdom (Steeley, 2001) which suggested a disappearing day-of-the-week effect starting from the 1990s and subsequently went through a period of time-varying market anomalies. There is no clear evidence of the presence of day-of-the-week anomalies in the stock market and which is a topic of ongoing debate. These conflicting findings indicate a need for further research to clarify the presence and nature of day-of-the-week anomalies in the BRICS and G5 stock markets.

4.2.2. Month of the year effect

The month-of-the-year effect, also known as the January effect or the other-month effect, is another calendar anomaly that has been extensively studied in finance literature. It refers to the tendency of stock returns to exhibit patterns or variations across different months of the year. Rozeff and Kinney's (1976) studies on the month-of-the-year effect have been well-received by practitioners and academics. They found that average stock returns in the NYSE were significantly higher in January (3.48%) compared to other months of the year (0.42%). This phenomenon became known as the "January effect". The tax-loss selling hypothesis was attributed to this effect, as investors tend to sell at the end of the year. By strategically realizing losses for tax purposes in December and subsequently rebalancing their portfolios in January, investors inadvertently contribute to the observed January effect in stock returns (Ritter, 1988; Dahlquist & Sellin, 1994). Ignatius (1992) investigated the presence of the January effect in the Indian and U.S. stock markets. Through his study, he found evidence supporting the existence of this effect in both the markets. Aggarwal and Rivoli (1989) conducted a study that identified a seasonal pattern in emerging stock returns, higher returns during the month of January, across Hong Kong, Singapore, Malaysia, and the Philippines. Choudhry (2001) also confirmed the January effect in seven emerging markets, including Argentina, Brazil, Mexico, Greece, India, Pakistan, and Zimbabwe. Subsequent studies have confirmed the existence of the January effect in various international stock markets, including the U.S. (Gultekin & Gultekin, 1983; Haugen & Jorion, 1996), the Canada (Berges et al., 1984), the U.K. (Reinganum & Shapiro, 1987), several other European countries (Agrawal & Tandon, 1994; Wen & Li, 2016), South African (Alagidede, 2013), and Chinese (Wang et al., 2013)

However, some studies have also identified other month-of-the-year effects, such as the "sell in May and go away" anomaly, which suggests that stock returns tend to be lower during the summer months (May to October) compared to the winter months (November to April) and the October effect (Alrabadi & Al-Qudah, 2012; Bouman & Jacobsen, 2002; Dichtl & Drobetz, 2014). According to the study conducted by Choudhary (2001) German market show no January effect and month of the other effect was found UK and US markets using GARCH model. Agrawal and Tandon (1994) identified higher returns in April and lower returns in September in several Asian markets, including India, South Korea, Malaysia, and the Philippines. The result is similar to the finding of Ignatius (1992). Ciccone and Etebari (2008) provides a comprehensive overview of the existing research on the month-of-the-year effect, emphasizing the significance of the January and September effects across various international stock markets, including the U.S., France, Germany, the U.K., and Japan. Evidence of the September effect was found in recent studies by Bajaj et al. (2019) and Acharya et al. (2024), in which significant higher returns in the Indian stock market during the month of September compared with other months of the year.

Agarwal and Jha (2023) conducted a study in six emerging markets and found evidence of higher returns in February, April and July and lower returns in December in case of Korean, Indonesian and Malaysian stock markets. Mangala and Lohia (2013) conducted the month-of-the-year effect in stock index returns and volatility across emerging stock markets using GARCH (1,1). The findings reveal a significant positive mean return during the months around the end of the year and the beginning of the new year, indicating the presence of a November, December, and January effect in the stock markets of Argentina, India, Malaysia, and Russia. Additionally, the study identifies statistically significant negative mean coefficients for the months of August and September, representing the third quarter of the year, across a majority of the emerging markets examined.

While the month-of-the-year effect has been widely observed, its profitability and persistence over time have been debated. Some studies have found that the January effect has diminished or become less pronounced in recent years, potentially due to increased market efficiency and the widespread recognition of this anomaly by market participants (Haugen & Jorion, 1996; Marquering et al., 2006). Recent studies (Plastun et al., 2019; Plastun et al., 2020; Rossi & Gunardi, 2018) also further claim that calendar anomalies disappear, and therefore, there is no evidence of exploitable profit opportunities based on them that would be inconsistent with market efficiency. Moreover, Darrat et al. (2011), look into a context of 34 international stock over a period from 1988 to 2010, in contrast to previous studies, the researchers found no significant evidence of the January effect across most of the markets examined, except for Denmark, Ireland, and Jordan. Instead, their findings revealed a significant and positive return anomaly during the months of December and April across a vast majority of the markets under consideration. Furthermore, the study identified significant negative return anomalies during the months of June, August, and September in their sample. These results challenge the widely documented January effect and suggest that calendar-based stock market anomalies may manifest differently across various market contexts and time periods, deviating from the previously established patterns observed in earlier research. Nevertheless, the month-of-the-year effect remains an important area of research in finance, as it challenges the notion of market efficiency and has implications for asset pricing, portfolio management, and investor behaviour. Despite the mixed findings across different markets and time periods, the persistent observation of calendar-based anomalies in stock returns warrants further investigation. Understanding the underlying drivers and mechanisms behind these anomalies could shed light on the potential market inefficiencies, investor irrationality, or risk-based explanations that contribute to these recurring patterns.

4.2.3. Turn of the month effect

The turn of the month (TOM) effect is one of the calendar anomalies that has been documented over decades. One of the earlier documented calendar anomalies, was first empirically examined by Ariel (1987) in his seminal study on the US stock market. The study's findings suggested that the TOM outperformance, characterized by the elevated returns during the (-1, +9) period, referred to as the first half of the month (FH), was persistent and statistically outperform the returns for the entire month. Lakonishok and Smidt (1988) also confirmed the existence of the turn-of-the-month effect and suggested that it might be related to the payment of monthly salaries and the subsequent reinvestment of funds by individual investors. Lakonishok and Smidt (1988) documented TOM using an extensive study over a period of 90 years data from Dow Jones Industrial average, thus show mean returns during TOM are significantly higher during the time span (last day trading and first three trading day of the month i.e. -1, +3) than during the remain day of the month (ROM). This result sustenance to the earlier finding (Agarwal & Tandon, 1994; Cadsby & Ratner,1992; Kunkel, et al., 2003; McConnell & Xu 2008) that stock market returns concentrated in a few days at the end and initial period of the month. Cadsby and Ratner (1992) conducted a study on the persistence of turn-of-month effect on ten developed countries over a period from 1962 to 1982. They found stock returns tend to be significantly higher at the beginning of a new month in Canada, United Kingdom, Australia, Switzerland, and West Germany. Agrawal and Tandon (1994) examined the turn of the month effect across 18 countries covering major developed markets as well as some emerging markets over different sample periods ranging from the 1970s to the early 1990s. The found that a significant higher return around the TOM were documented in developed and emerging markets. the study provided evidence that calendar anomalies are not merely illusions but reflect systematic patterns in stock returns that cannot be fully rationalized by existing asset pricing models. Kunkel, et al., (2003) examined the persistence of the turn-of-the-month (TOM) effect in daily stock returns across 19 country stock market indices from 1988 to 2000. The study questions the validity of standard parametric tests (ANOVA) and considers nonparametric (Wilcoxon signed rank test) methods as powerful alternatives. They found that the TOM effect is not limited to specific regions but is evident in Europe, the Far East, North America, and South Africa. McConnell and Xu (2008) extended the earlier research by Lakonishok and Smidt (1988) using 109-year period of U.S. stocks. Their findings confirmed the persistence of the turn-of-the-month effect, even with the expanded sample period spanning over a century from 1897 to 2005. Their analysis unveiled that the entire positive equity return for stocks in the DJIA was concentrated during the turn-of-the-month interval, asserting that investors did not receive any compensation for bearing market risk except during the TOM. Their evidence suggested that the anomaly was a broader phenomenon, manifesting in 31 out of the 35 countries examined.

Some of other studies that also claimed that the persistence of turn-of-the-month effect include; Liu, (2013); Vasileiou, (2013); Sharma & Narayan, (2014); Kayacetin & Lekpek, (2016); Aziz & Ansari, (2017); Arendas & Kotlebova, (2019); Singh et al., (2020). Vasileiou (2013) examined the impact of financial trends and economic cycles on the TOM effect in the Greek stock market. The study employed a TGARCH asymmetry model, selected for its suitability in capturing leverage effects. The findings revealed a robust TOM effect in the Greek market, influenced by financial trends and volatility shifts. Notably, even during recessionary periods, TOM days demonstrated positive returns. The study highlights the persistence of the TOM anomaly and its potential interplay with market conditions. Sharma and Narayan (2014) studied whether TOM effect depends on sector and size of the firm by taking an observation of 560 listed NYSE listed stock. Their findings confirmed the existence of the TOM effect across these markets, with the highest returns consistently occurring during the (-1, +3) period. The finding is similar to earlier finding of Liu (2013) on US equity market. Kayacetin & Lekpek (2016) analysed ToM effect in emerging stock in Turkish equity return over 1988-2014 for a duration of -10 to +10. The study employed a comprehensive methodology, including mean daily return analysis, sub-period examination, conditional volatility dynamics investigation, and trading volume analysis around TOM, and controlling for other seasonal patterns. The findings revealed a highly significant TOM effect, with mean daily returns of 0.46% during the TOM period compared to 0.09% in the rest of the month. The effect was strongest in April, following the release of annual financial statements, suggesting a link to information risk. The results support the information risk hypothesis, where gradual uncertainty resolution before month-end leads to higher equity returns, especially after positive news preceding the TOM period. The study by Aziz and Ansari (2017) investigated TOM effect across 12 major Asia-Pacific markets from January 2000 to April 2015, considering a TOM duration of -7 to +7 days. Employing parametric tests, a GARCH (1, 1) model, and the non-parametric Wilcoxon Signed Rank (WSR) test, the research found a significant TOM effect in 11 out of the 12 markets, independent of the turn-of-the-year effect. The anomaly persisted throughout the sample period, indicating a long-standing pattern in equity returns. However, the TOM effect was not statistically significant during the financial crisis period. Arendas et al. (2019) examined the stock markets of 11 Central and Eastern European (CEE) countries over a 20-year period spanning from January 1997 to December 2016. The methodology employed in the research involved dividing trading days into TOM and Rest-of-the-Month (ROM) periods, calculating daily returns and volatilities, and evaluating the statistical significance of differences in returns and volatilities between TOM and ROM periods using both parametric and non-parametric tests. The findings of the study revealed that the TOM effect was statistically significant in seven out of the 11 investigated CEE countries. Notably, the Slovak and Latvian stock markets exhibited distinct behaviour compared to the majority of CEE stock markets in terms of the TOM effect. The authors highlighted that the presence of the TOM effect contradicts the efficient markets hypothesis, indicating that the affected stock markets may not be efficient. Singh et al. (2021) examined (-1, +3) ToM effect in three major emerging equity markets: Brazil, India, and China using Ordinary Least Squares (OLS) regression with controlling for the day-of-the-week effect. The findings revealed a significant TOM effect in all three countries for the full sample period. However, the TOM effect exhibited variations across different sub-periods. Specifically, the anomaly disappeared during the global financial crisis (GFC) period in Brazil and India but remerged in the post-GFC period. The study provides empirical evidence supporting the existence of the TOM effect in emerging market and also highlighting its time-varying nature and potential implications for market efficiency and trading strategies.

The existence and persistence of TOM effect have been widely documented across various markets and time periods. However, there have been critics and studies that challenge the robustness of this anomaly, suggesting that it may have diminished or disappeared over certain time frames. These contrasting findings have sparked debates within the academic community and necessitated further investigation. One notable study by Horowitz et al. (1999) examined the relationship between monthly returns and the size effect in the NYSE, AMEX, and Nasdaq markets from 1963 to 1997. Employing mean return analysis and cross-sectional regressions, the authors identified the disappearing size effect, raising questions about the persistence of seasonal anomalies. Similarly, Agarwal and Tandon (1994) reported that daily seasonal anomalies largely disappeared in the 1980s, potentially indicating a shift in market dynamics. Maberly and Waggoner (2000) conducted a study in the US market over a seventeen-year period from 1982 to 1999 and concluded that the TOM effect disappeared after 1990, challenging its continued existence in the more recent period. Caporale and Plastun (2017) analysed various calendar anomalies in the Ukrainian stock market and found no significant presence of the TOM effect resulting in further questioning its universality across different markets. Kumar (2015) studied the presence of calendar anomalies in 20 currencies against the US dollar using ordinary least squares with a GARCH (1,1) model for a period of 19 years. The study claimed that calendar anomalies exhibited a disappearing trend in the later sample period, from 2005 to 2014, suggesting a potential diminishing effect over time. Similarly, Khan and Rabani (2018) used conventional approaches to study calendar anomalies in Japanese stock returns, covering data from 1977 to 2017. Their findings indicated the disappearance of calendar anomalies in the TOPIX index, further contributing to the debate on the persistence of such effects. Considering the ongoing discourse surrounding the turn-of-the-month effect and other calendar anomalies necessitates continuous investigation to gain a better for understanding. While numerous empirical studies have documented their existence, contrasting findings suggest that these anomalies may be time-varying or market-specific, potentially influenced by changes in market dynamics, investor behaviour, or other underlying factors. The debate emphasizes the need for continuous empirical investigation and the consideration of various methodologies, time periods, and market contexts to gain a comprehensive understanding of the turn-of-the-month effect and its implications for market efficiency.

4.2.4. Empirical Research Gap

The empirical results from market anomalies have remained inconclusive, with no clear consensus emerging from the diverse techniques and approaches employed by researchers. Despite extensive investigation, the existence and persistence of calendar effects remain a topic of ongoing debate within the academic literature. The mixed findings across different markets and the disappearance of anomalies in certain markets emphasise the need for further investigation. Empirical research indicates that time-varying or market-specific anomalies remain largely unexplored within the context of the selected market sample. This gap is particularly evident when extending the analysis to the BRICS and G5 markets, in which distinct market dynamics and structural differences may influence the presence and characteristics of such anomalies. Further gaps arise from the inconclusive evidence obtained by examining long-memory stock returns. This study addresses a significant gap in the extant literature by systematically investigating market anomalies across three decades of data from emerging and developed markets. Furthermore, by employing a fixed window approach to disaggregate the data, we provide a more granular analysis of time-varying calendar effects, thereby offering novel insights into the patterns and characteristics of the anomalies under examination. Based on the research gap outlined above, the following hypotheses were formulated:

H2: The stock market exhibits significant calendar anomalies

H2a: There is a significant day-of-the-week effect on BRICS and G5 market returns

H2a: There is a significant month-of-the-year effect on the BRICS and G5 market returns

H3a: There is a significant turn-of-the-month effect on the BRICS and G5 market returns

H3: There is a significant adaptive nature of calendar effects

H3a: There are significant time-varying calendar effects in BRICS financial markets

H3b: There are significant time-varying calendar effects in G-5 financial markets

H3c: The adaptive patterns of calendar effects differ between G-5 and BRICS markets

4.3. Methodology

4.3.1. Model specification

When investigating calendar anomalies in stock returns, we conduct a test on the mean and variance returns to determine if there is a significant day-of-the-week effect, turn-of-the-month effect, or month-of-the-year effect that differs from other trading days. In this case, the standard ordinary least squares (OLS) regression equation with dummy variables is unsuitable for studying the effect on returns. The OLS model has a drawback with the assumption that the variance error term is constant over time. This leads to inaccurate confidence intervals, statistical tests, and skewed estimates of the standard error and coefficients. Furthermore, the error term has a non-normal distribution and the volatility of stock returns varies over time, neither of which can be captured by the usual OLS model (Connolly, 1989). A conditional heteroskedasticity can be incorporated by allowing variances of errors to be time-dependent on the stock return (Bollerslev, 1986). As a result, error terms will have a mean of (0) zero and a variance that varies over time $h_t^2[\varepsilon_t \sim (0, h_t^2)]$. Therefore, to address non-normal error terms, the robustness standard GARCH model of Bollerslev (1986) and the asymmetric GARCH of Nelson (1991) have been applied. GARCH models allow for the assumption of non-constant and non-normally distributed returns and explains the clustering of volatility in the data collected across time series for any financial asset. The mean equation and variance equation of the of GARCH (p, q) model shown below:

$$R_{i,t} = \omega + \sum_{i=1}^{n} \beta_i D_i + \varepsilon_t \tag{4.1}$$

Where, $R_{i,t}$is the daily returns of the stock, $\sum_{i=1}^{n} D_i$ represent dummy variables for all the calendar anomalies and β_i measure the daily return of the respective anomalies. ε_t is the error term. The variance equation σ_t^2, which in turn represents the conditional variance equation as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 + \sum_{i=1}^{n} D_n + \varepsilon_t \tag{4.2}$$

$$\varepsilon_t \sim GED\ (0, h_t) \tag{4.3}$$

Where, σ_t^2 is the conditional variance, ε_{t-1} is the innovation, $\alpha_i \varepsilon_{t-i}^2$ represent the ARCH term, $\beta_i \sigma_{t-j}^2$ represent the GARCH term. D_n represent the dummy variables for each of the calendar anomalies. The number of the autoregressive term is determined using the Schwarz or BIC criterion. ε_t follows the generalised Error Distribution (GED) with mean zero and conditional variance h_t suggested by Nelson (1991). The EViews legacy technique is utilised to maximise the log-likelihood function of the GED. The GARCH model with GED distribution has a minimal mean square error (MSE) and outperforms in GARCH model estimation (Kumar and Patil, 2016).

The GARCH model exhibits a significant limitation due to its symmetric nature. As the variance equation squares the error term, the signs of the error term are disregarded and fail to capture asymmetry. An additional constraint is that the response must be positive and the negative financial shocks must be symmetrical. In fact, financial markets exhibit both positive and negative shocks. This asymmetry is referred to as the leverage effect in finance. In financial time series analysis, the asymmetry effect denotes the characteristic of time series on asset prices and suggests that negative news tends to increase volatility more than positive news (Black, 1976). As for the asymmetric EGARCH (1,1) proposed by Nelson (1991) model allows to measure the leverage effect. The conditional variance equation of EGARCH effect is expressed as:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sqrt{\sigma_{t-k}^2}} + \sum_{i}^{p} \alpha_i \left[\frac{|\mu_{t-k}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}}\right] + n \sum_{j=1}^{n} Dum_t \tag{4.4}$$

Where, $\ln(\sigma_t^2)$ is the conditional variance of return at time (t). $\beta_j \ln\left(\sigma_{t-j}^2\right)$ is the conditional variance at time (t-1), $\alpha_i \left[\frac{|\mu_{t-k}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}}\right]$ is the effect of the shock (i.e news information on good or bad news) on conditional variance. $\gamma_k \frac{\mu_{t-k}}{\sqrt{\sigma_{t-k}^2}}$ is the effect of positive and negative shock on the conditional variance (Leverage effect), $\sum_{j=1}^{n} Dum_t$ is a set of dummy variable taken the value of 1 on the respective calendar anomalies.

One of the reasons why the EGARCH model is becoming increasingly popular is the way it captures both conditional positive and negative effects of equal magnitude and leverage effects that are both asymmetric. That is negative correlation exists between returns shocks and subsequent changes (McAleer & Hafner, 2014). In contrast to the GARCH model, the EGARCH model does not have any restrictions on the coefficients that cannot be negative, as compared to the GARCH model. There is not a conflict of interest between the leverage effect of positive and negative shocks on the conditional variance, because the sign of the parameter is expected to be negative if the relationship between return and volatility is negative. EGARCH can be used to test the leverage effect by hypothesising that the impact is asymmetric if $\gamma \neq 0$. For estimation optimisation, the equation estimation utilised the EViews legacy technique to maximise the log-likelihood function of the GED. The GARCH model with a GED distribution has a minimal mean square error (MSE) and outperforms the GARCH model estimation (Kumar & Patil, 2016).

4.3.2. The Day of the Week effect

Day-of-the-week assumed that particular day generates abnormal returns. The day-of-the-week effect in the study was estimated by using the following model.

$$R_{it} = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + D_{4i} + \beta_5 D_{5i} + \varepsilon_{it} \quad (4.5)$$

where, R_{it} is the daily return for BRICS and G7 countries stock indices (i). $\beta_1 D_{1i}$ to $\beta_5 D_{1i}$ are dummy variables for each of the five day-of-the-week for emerging and developing stock indices (i). Taking the value of 1 for each day of the week, if day t is a Monday, D_1 will take a value of 1, otherwise 0 and so on for the day-of-the-week. The null hypothesis H_{02a}: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$ (No day-of-the-week effect in returns) or specifically for Monday effect: H_{02a}: $\beta_1 = 0$ (No Monday effect). β_1 to β_4 are coefficient for corresponding day-of-the-week effect and ε_{it} is the error term.

The GARCH (1,1) specification of the model is expressed as follows

$$R_{i,t} = \beta_0 + \sum_{n=1}^{5} \beta_1 D_1 + \sum_{n=1}^{5} \beta_2 D_2 + \sum_{n=1}^{5} \beta_3 D_3 + \sum_{n=1}^{5} \beta_4 D_4 + \sum_{n=1}^{5} \beta_5 D_5 + \varepsilon_t \quad (4.6)$$

$$\varepsilon_t \sim GED\ (0, \sigma_t^2) \quad (4.5b)$$

Where, $\sum_{n=1}^{5} \beta_n D_n$ represent dummy variables for all the day-of-the-week. β_1 to β_5 are coefficients for the corresponding day-of-the-week effect. The variance equation σ_t^2, which in turn represents the conditional variance equation is as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 + \sum_{n=1}^{5} \beta_n Dum_n + \varepsilon_t \quad (4.7)$$

Where, R_{it} is the daily stock return of specific countries stocks under study (i). D_n is the dummy for the day that take on the value of one specific day and zero otherwise. To avoid spurious results on dummy traps, the DOW effect was analysed separately for each trading day from Monday (d=1) to Friday (d=5). In this case all the trading day calendar anomalies can be computed without encountering econometric problem due to extensive dummy variable. α_i represent the ARCH term and β_i is the GARCH model. For volatility (variance equation), the null hypothesis H_{02a}: $\sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5$ (No day-of-the-week effect in volatility) or specifically for Monday volatility: H_0: $\sigma_1 = 0$ (No Monday volatility effect)

The EGARCH (1,1) specification for day-of-the-week effect is expressed as follow:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sqrt{\sigma_{t-k}^2}} + \sum_{i}^{p} \alpha_i \left[\frac{|\mu_{t-k}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}}\right] + n \sum_{t=1}^{n} Dum_t \tag{4.8}$$

where, Dum_t is the dummy set that take that value of 1 on the respective day-of-the-week and zero otherwise.

4.3.3. Month of the year effect

Monthly effect on January (Rozeff & Kinney, 1976) was one of the earlier types of evidence to find abnormal higher returns than other months. Since then, numerous investigations have proved the occurrence of such anomalies Roll (1983), Reinganum (1983). However, this January anomalies have been observed to appear less over time. In this, instead of conducting the turn of the year effect, we conducted the monthly effect. To examine the monthly effect, a dummy variable was created each month of the year. The ordinary least square estimation is used to study the monthly effect. The regression equation is specified as follows:

$$R_{i,t} = \beta_0 + \beta_1 M_1 + \beta_2 M_2 + \beta_3 M_3 + \beta_4 M_4 + \beta_5 M_5 + \beta_6 M_6 + \beta_7 M_7 + \beta_8 M_8 + \beta_9 M_9 + \beta_{10} M_8 + \beta_{11} M_{11} + \beta_1 M_{12} + \varepsilon_{it} \tag{4.9}$$

Where, $R_{i,t}$ = the return of stock indices on day (t) on the major stock exchange in India (i). where, M_1 to M_{12} are dummy variables for month dummy, taking the value of 1 for each month, otherwise 0. β_1 to β_{12} are coefficient for corresponding holiday effect and ε_t is the error term.

The GARCH (1,1) specification of the model is expressed as follows

$$R_{i,t} = \beta_0 + \sum_{n=1}^{12} \beta_1 D_1 + \sum_{n=1}^{12} \beta_2 D_2 + \cdots \ldots \ldots \ldots \ldots .. + \sum_{n=1}^{12} \beta_n D_n + \varepsilon_t \qquad (4.10)$$

$$\varepsilon_t \sim GED\ (0, \sigma_t^2) \qquad (4.10a)$$

Where, $\sum_{n=1}^{12} \beta_n D_n$ represent dummy variables for all month starting from January. β_1 to β_5 are coefficients for the corresponding month of the year effect. The variance equation σ_t^2, which in turn represents the conditional variance equation is given as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 + \sum_{n=1}^{12} \beta_n Dum_n + \varepsilon_t \qquad (4.11)$$

Where, D_n is the dummy for the day that take on the value of one on a specific month and zero otherwise. α_i represent the ARCH term and β_i is the GARCH model.

The EGARCH (1,1) specification for month of the year effect is expressed as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sqrt{\sigma_{t-k}^2}} + \sum_i^p \alpha_i \left[\frac{|\mu_{t-k}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}}\right] +$$

$$n \sum_{t=1}^{n} Dum_t \qquad (4.12)$$

where, Dum_t is the dummy set that takes the value of 1 on the respective month of the year and zero otherwise.

4.3.4. Turn of the month effect

There is no consensus regarding the precise TOM. The TOM effect was conducted using various window lengths. The last trading day of the previous month and the first eight days of the subsequent month were used by Ariel (1987).

Lakonishok and Smidt (1988) used the last four trading days and the first three trading days. The last and first four trading days were used by Liu (2013), and the last two and first four trading days of each month were used by Kayacetin and Lekpek (2016). Arendas and Kotlebova (2019) used different lengths using an equal day of the last day and the first trading day of the month (i.e. 1+1, 2+2, and 3+3). We investigate alternative turn of the month window, using Ariel (1987), Lakonishok and Smidt (1988) and our estimation of turn of the month that covers the last day and the fifth trading day of a month (TOM_1) [-1, +5] and the last 5 trading days and the first trading day (TOM_2) [-5, +1].

The specification of the model utilized in the turn of the month effect are shown below:

$$R_{i,t} = \beta_0 + \beta_1 TOM_A + \beta_2 TOM_{LS} + \beta_3 TOM_1 + \beta_4 TOM_2 + \varepsilon_t \quad (4.13)$$

Where, TOM_A represent dummy variables for Ariel (1987), TOM_{LS} represent dummy variables for Lakonishok and Smidt (1988), TOM_1 represent the last day and the fifth trading day of a month and TOM_2 represent the first trading day and the fifth trading day of the previous month. The constant term is represented in β_0. β_1 to β_4 are coefficients for the corresponding turn of the month effect. The variance equation σ_t^2, which in turn represents the conditional variance equation is as follows:

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \ + \sum_{n=1}^{11} \beta_n D_n + \varepsilon_t \quad (4.14)$$

$$\varepsilon_t \sim GED\ (0, \sigma_t^2) \quad (4.14a)$$

The EGARCH (1,1) specification for month of the year effect is expressed as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sqrt{\sigma_{t-k}^2}} + \sum_{i}^{p} \alpha_i \left[\frac{|\mu_{t-k}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right] + n \sum_{t=1}^{n} Dum_t \quad (4.15)$$

where, Where, R_{it} is the daily stock return of specific countries stocks under study (i). D_n is the dummy turn of the month on the value of one specific day and otherwise 0.

Dum_t is the dummy set that takes the value of 1 on the respective turn of the month and otherwise 0.

4.3.5. Data

The data used in this study comprise of the daily closing price of primary stock market index for the BRICS countries and a group of seven (G-5) countries similar with the previous Chapter 3. The logarithmic daily percentage return for the sample period is determined by applying the following equation (4.18).

$$R_{i,t} = \frac{R_t - R_{t-1}}{R_{t-1}} \times 100 \tag{4.18}$$

Where $R_{i,t}$ is the index return, ln is the natural log of the underlying market series, R_t is the closing value of a given index on a specific trading day, and R_{t-1} is the closing value of a given index on the previous day (t–1).

4.3.6. Descriptive Statistics

The analysis of day-of-the-week effects across BRICS markets in Table 4.1 reveals diverse patterns of calendar anomalies. In the Indian market (BSE SENSEX), while Wednesday (0.086%) shows the highest mean return, no statistically significant differences in means are observed across weekdays at 5 percent and 10 percent. Further, KS- statistic show Monday and Wednesday are notably distinct. The SSE Composite exhibits more pronounced effects, with Friday yielding the highest mean return and Thursday the lowest, accompanied by statistically significant differences in means for these days and distinct return distributions for most weekdays. The same has been further strengthened by significant Thursday and Friday. Brazil's IBOVESPA displays an unusually high mean return and volatility on Tuesdays, with significant differences in means for both Monday and Tuesday, suggesting strong day-of-the-week effects. South Africa's JALSH shows a gradual decline in mean returns from Monday to Friday, with Friday exhibiting a significant positive difference in means and distinct return distributions on Mondays and Fridays. The Russian market (MOEX) presents the highest mean return on Mondays and the lowest on Wednesdays, with Wednesday showing a significant positive difference in means and Monday having a distinct return distribution.

Descriptive statistics of day-of-the-week effects across the G5 markets are presented in Table 4.2. The CAC 40 market shows the highest mean return (0.0372%) in Tuesday and no statistically significant differences in means or return distributions were observed. The German market DAX 30 exhibits the highest mean return on Wednesday (0.061%) and lowest on Thursday (-0.011%), though no days show statistically significant differences in means or return distributions. The UK market (FTSE 100) displays more pronounced effects, with Tuesday yielding the highest mean return (0.063%) and Thursday yielding the lowest (-0.041%). Tuesday shows a significant negative difference in means at the 5 percent level, whereas Thursday shows a significant positive difference at the 1 percent level. The KS test also indicated a distinct return distribution for Thursday at the 10 percent significance level. Japan's NIKKEI 225 presents the highest mean return on Tuesdays and Thursdays (0.031%), and the lowest on Mondays (-0.056%). Mondays show a significant positive difference in means at the 1% level and a distinct return distribution according to the KS test at the 1% significance level. The US market (S&P 500) shows the highest mean return on Tuesdays (0.062%) and the lowest on Thursdays (0.008%). Both Tuesday and Wednesday exhibited significant negative differences in the means at the 1% level. The KS test indicated a distinct return distribution for Monday at the 1 percent significance level.

Table 4.1: Descriptive statistic of BRICS market day of the week calendar anomaly

	Monday	Tuesday	Wednesday	Thursday	Friday
Panel A: BSE SENSEX					
Mean	0.028	0.057	0.086	0.023	0.067
Standard deviation	1.857	1.548	1.508	1.483	1.581
No. of days effect	1587	1591	1597	1594	1573
t-statistics	0.722	-0.082	-0.894	0.872	-0.35
KS- statistics	0.041**	0.03	0.035***	0.023	0.023
Panel B: SSE Composite					
Mean	0.042	0.0212	0.103	-0.109	0.16
Standard deviation	2.295	2.649	2.079	1.949	1.87
No. of days effect	1,558	1,584	1,592	1,589	1,575
t-statistic	0.028	0.45	-1.22	3.11*	-2.373**
KS- statistics	0.059*	0.047*	0.026	0.073**	0.035**
Panel C: IBOVESPA					
Mean	0.014	0.697	0.224	0.111	0.229
Standard deviation	2.421	19.031	2.16	2.752	2.509
No. of days effect	1,491	1,490	1,572	1,535	1,529
t-statistic	1.258***	-2.111**	0.231	0.793	0.197
KS- statistics	0.046	0.033	0.029	0.021	0.032
Panel D: JALSH					
Mean	0.064	0.047	0.042	0.035	0.003
Standard deviation	1.263	1.184	1.217	1.226	1.141
No. of days effect	1,378	1,413	1,410	1,414	1,401
t-statistic	-0.885	-0.311	-0.15	0.108	1.217**
KS- statistics	0.057*	0.013	0.025	0.021	0.038***
Panel E: MOEX					
Mean	0.111	0.063	-0.031	0.018	0.066
Standard deviation	2.594	2.538	2.324	2.613	2.244
No. of days effect	1,211	1,270	1,272	1,275	1,254
t-statistic	-0.99	-0.243	1.291**	0.493	-0.289
KS- statistics	0.05**	0.022	0.035	0.029	0.029

Source: *Author's computation Using Stata*

Note(s): This table represents the descriptive statistics of day of the week calendar anomaly. KS represent the Kolmogorov-Smirnov that allows to detect patterns you cannot detect with a student's t-test. *, **, ***, indicates level of significance at the 1%, 5% and 10% level respectively.

Table 4.2: Descriptive statistic of G5 market day of the week calendar anomaly

Panel A: CAC 40					
BSE	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.017	0.0372	0.02	0.0129	0.016
Standard deviation	1.509	1.317	1.303	1.396	1.339
No. of days effect	1,689	1.317	1,711	1,711	1,691
t-statistic	1.054	-0.787	-0.217	0.028	-0.073
KS- statistics	0.019	0.018	0.016	0.018	0.0103
Panel B: DAX 30					
Mean	0.053	0.015	0.061	-0.011	0.014
Standard deviation	1.58	1.417	1.361	1.407	1.336
No. of days effect	1,647	1,685	1,689	1,673	1,661
t-statistic	-0.927	-1.176	-1.186	1.167	0.309
KS- statistics	0.021	0.02	0.029	0.021	0.022
Panel C: FTSE 100					
Mean	0.003	0.063	0.011	-0.041	0.029
Standard deviation	1.158	1.04	1.065	1.104	1.097
No. of days effect	1,654	1,691	1,696	1,687	1,685
t-statistics	0.396	-2.117*	0.121	0.161**	-0.697
KS- statistics	0.047	0.028	0.022	0.033***	0.029
Panel D: NIKKEI 225					
Mean	-0.056	0.031	0.013	0.031	-0.033
Standard deviation	1.601	1.447	1.431	1.474	1.447
No. of days effect	1,541	1,650	1,652	1,649	1,658
t-statistic	1.61**	-1.052	-0.488	-1.005	0.968
KS- statistics	0.045**	0.027	0.022	0.024	0.021
Panel D: S&P 500					
Mean	0.019	0.062	0.041	0.008	0.033
Standard deviation	1.275	1.161	1.094	1.16	1.172
No. of days effect	1,574	1,706	1,702	1,679	1,665
t-statistic	0.346	-1.378**	-0.507**	0.773	0.772
KS- statistics	0.022**	0.025	0.021	0.017	0.021

Source: *Author's computation Using Stata*

Note(s): This table represents the descriptive statistics of the day of the week calendar anomaly. KS represent the Kolmogorov-Smirnov that allows to detect patterns you cannot detect with a Student's T-Test. *, **, ***, indicates level of significance at the 1%, 5% and 10% level respectively.

The descriptive statistics of Month of the year anomaly in BRICS and G5 Market is presented in Table 4.3. Panel A of Table 4.3 represent the BRICS market. The IBOVESPA market shows the highest mean return (0.226%) and volatility (standard deviation of 3.054). MOEX market follows with a mean return of 0.12%. JALSH and SSEC show moderate positive returns, while SENSEX has the lowest mean return (0.007%). However, none of the BRICS markets exhibit statistically significant differences in means for January returns compared to other months. The

Kolmogorov-Smirnov (KS) test also doesn't indicate significant differences in return distributions for January in any of the BRICS markets. DAX 30 market shows the highest mean return in January (0.023%), followed by CAC 40 (France) at 0.009%. Interestingly, FTSE 100 (UK) and NIKKEI 225 (Japan) show negative mean returns in January (-0.035% and -0.034% respectively). The S&P 500 (USA) shows a very slight positive mean return (0.0011%). Only the FTSE 100 exhibits a statistically significant difference in means for January returns at the 5% level, with a positive t-statistic of 1.35. This suggests a potential reverse January effect in the UK market. The KS test doesn't indicate significant differences in return distributions for January in any of the G5 markets.

Table 4.3: Descriptive statistic of BRICS and G5 market month of the year calendar anomaly

Panel A: BRICS markets					
	SSEC	IBOVESPA	JALSH	MOEX	SENSEX
Mean	0.026	0.226	0.073	0.12	0.007
Standard deviation	1.836	3.054	1.167	2.463	0.792
No. of days effect	629	636	584	462	681
t-statistic	0.203	0.129	-0.727	-0.651	0.792
KS- statistics	0.034	0.031	0.034	0.051	0.045
Panel B: G5 Markets					
	CAC 40	DAX 30	FTSE 100	NIKKEI225	S&P 500
Mean	0.009	0.023	-0.035	-0.034	0.0011
Standard deviation	1.292	1.343	1.021	1.578	1.058
No. of days effect	716	708	711	638	681
t-statistic	0.089	0.024	1.35**	0.574	0.697
KS- statistics	0.038	0.026	0.051	0.04	0.026

Source: *Author's computation Using Stata*

Note(s): This table represent the descriptive statistics of month of the year calendar anomaly of January effect. Representing of all month of the year effect will result in ambiguous, so, January effect is shown in the table to identify the month of the year effect is presented and Researchers often focus on the January effect as a proxy for the month-of-the-year effect. KS represent the Kolmogorov-Smirnov that allows to detect patterns you cannot detect with a student's t-test. *, **, ***, indicates level of significance at the 1%, 5% and 10% level respectively.

The descriptive of turn-of-the-month effects for BRICS markets is presented in Panel A of Table 4.4. The SENSEX shows significant turn-of-the-month effects, with LS model having the highest mean return (0.139%) and t-statistic (-3.44) significant at the 1% level. The KS statistics are significant for all models, indicating distinct return distributions during the turn of the month. IBOVESPA displays high returns and volatility compared to other markets, with the TOM2 [-1, +5] showing the highest mean return (0.618%). The KS statistics are significant for LS, TOM_1, and TOM_2 models, indicating non-normal return distributions. The Chinese market (SSEC) shows varied results across models, with TOM_1[-5, +1] yielding the highest mean return (0.172%) and a highly significant t-statistic (-3.352). KS statistics are significant for all models except TOM_2, suggesting distinct return distributions during the anomaly period. The JALSH demonstrates consistent evidence mean different turn-of-the-month effects across all models and KS statistics are significant for most models, indicating non-normal return distributions. The MOEX show significant mean return during turn-of-the-month in three out of four models, with TOM_1 showing the highest mean return (0.232%) and significant t-statistics. The KS statistics of MOEX show significant for all models except TOM_2, suggesting distinct return distributions during the turn of the month.

The Descriptive statistic of turn-of-the-month effects for G5 markets is presented in Panel B Table 4.5. CAC 40 and DAX 30 show significant effects in LS and TOM_2 models, with high mean returns and significant t-statistics. FTSE 100 demonstrates consistent effects across LS, TOM_1, and TOM_2 models. NIKKEI 225 exhibits weaker effects, with significance only in LS and TOM2 models. S&P 500 shows significant effects in LS and TOM_2 models. KS statistics are mostly significant, indicating non-normal return distributions, except for Ariel model except in FTSE 100 and NIKKEI 225 markets.

Table 4.4: Descriptive statistic of turn of the month anomaly on BRICS and G5 market

	Panel A: BRICS				Panel B: G5			
	Ariel	**LS**	**TOM$_1$**	**TOM$_2$**	**Ariel**	**LS**	**TOM$_1$**	**TOM$_2$**
	SENSEX				CAC 40			
Mean	0.078	0.139	0.13	0.138	0.002	0.101	0.041	0.107
Standard deviation	1.642	1.643	1.682	1.704	1.393	1.563	1.384	1.822
No. of days effect	3,626	2,772	2,376	2,376	4,356	2,772	2,376	2,376
t-statistics	-1.435**	-3.44*	-2.742*	-3.05*	0.732	-3.679*	-1.013	-3.551*
KS- statistics	0.036**	0.044*	0.045*	0.042*	0.022	0.051*	0.031***	0.055*
	IBOVESPA				DAX 30			
Mean	0.384	0.592	0.28	0.618	0.028	0.091	0.060	0.084
Standard deviation	2.30	2.456	2.715	2.437	1.428	1.401	1.431	1.402
No. of days effect	3,568	2,654	2,270	2,275	3,960	2,772	2,376	2,376
t-statistic	-1.251**	-2.361	-0.07	-2.273	-0.232	-3.064*	-1.459***	-2.474**
KS- statistics	0.021	0.054*	0.049*	0.045*	0.016	0.051*	0.037**	0.044*
	SSEC				FTSE 100			
Mean	0.098	0.118	0.172	0.0453	0.011	0.079	0.056	0.061
Standard deviation	1.02	2.448	2.037	2.542	1.106	1.073	1.103	1.087
No. of days effect	3,651	2,694	2,313	2,309	4,057	2,772	2,376	2,376
t-statistics	-2.387**	-2.17**	-3.352*	-0.041	0.245	-3.90*	-2.290**	-2.548**
KS- statistics	0.043*	0.038**	0.065*	0.024	0.022*	0.058*	0.047*	0.058*
	JALSH				NIKKEI 225			
Mean	0.064	0.088	0.099	0.081	-0.009	0.037	0.005	0.045
Standard deviation	1.184	1.197	1.162	1.219	1.495	1.446	1.449	1.441
No. of days effect	3,388	2,310	1,980	1,980	3,861	2,767	2,372	2,372
t-statistics	-1.86***	-2.41**	-2.662	-1.83***	0.426**	-1.788***	-0.354	-1.908**
KS- statistics	0.021**	0.045*	0.055	0.038**	0.022**	0.021	0.015	0.023
	MOEX				S&P 500			
Mean	0.101	0.141	0.232	0.111	0.024	0.080	0.041	0.077
Standard deviation	2.455	2.508	2.442	2.571	1.156	1.137	1.129	1.141
No. of days effect	2,986	2,126	1,824	1,824	3,987	2,772	2,376	2,376
t-statistics	-1.792***	-2.138**	-3.777*	-1.282	0.357	-2.901*	-0.661	-2.478**
KS- statistics	0.033***	0.048*	0.059*	0.032	0.012	0.032***	0.021	0.031**

Source: *Author's computation Using Stata*

Note(s): This table represent the descriptive statistics of turn of the month calendar anomaly for both BRICS and G5 markets. KS represent the Kolmogorov-Smirnov that allows to detect patterns you cannot detect with a Student's T-Test. *, **, ***, indicates level of significance at the 1%, 5% and 10% level respectively.

4. 4. Empirical Result

4.4.1. Day-of-the-week effect for BRICS markets

The day-of-the-week effect refers to the phenomenon where stock returns tend to exhibit a significant higher(lower) variation of return on a particular day-of-the-week (Monday effect or Friday effect). If the variation in returns across different days is not significant at the 10 percent level, it implies that the observed differences in returns across days provides no day-of-the-week effect in the stock index.

Table 4.3 represents the estimated equation on day-of-the-week effect in BRICS countries. The Monday effect was found to be significant in four counties i.e., SSE, IBOSEPA, JALSH and MOEX at one percent level of significance. The estimated coefficients of the Monday effect provide a positive effect on Chinese (0.078), South Africa (0.077), and Russian (0.114) market, which implies that Monday returns are higher than those of Friday returns. The negative significant return in Brazil (-0.196) stock suggest that Monday return are smaller than those of the other days. The estimated results for Russian show the highest return, while Brazil shows the lowest in return on Monday. The Monday return in Indian stock also show a positive return, however not significant. The result contradicts the negative Monday effect. The Tuesday return are significant in Chinese (0.103) and Brazil (0.191) stock market at 1 percent and 5 percent respectively. The Tuesday return are negative in the stock market of South Africa, Russia and India but are not significant. The result is similar to the earlier finding (Agarawal & Tandon, 1994; Dubois & Louvet, 1996; Kumari, 2006). No significant Wednesday effect was found in all the emerging market. The return on Thursday shows a negative return in Chinese (-0.136) and Russian stock (-0.065) at 1 percent and 5 percent respectively. Moreover, Thursday return shows the lowest among the other trading days, but they are not statistically significant. The Friday return shows statistical insignificance and show the lower return than the Monday return in most of the markets except Brazilian stock exchange. The result of our study is contradicted with a higher Fridays return than any other day-of-the-week and lower on Monday (Cross, 1973; Fama, 1980; Jaffe & Westerfield, 1985).

In Panel B of Table 4.3, we also analyse the estimation of the variance equation. The ARCH effect shows a positive significance in both the model. This implies that return of a particular day are affected by the previous price movement of the stock. Higher return in t-day resulting in higher return in the subsequent day t+1. The volatility persistence measure by β shows a significant and positive return at 1 percent level of significance. The volatility persistent is highest in South African stock exchange (0.893, 0.988) and lowest in Brazilian stock exchange (0.550, 0.558) in GARCH and EGARCH model. A significant ARCH and GARCH coefficient indicate that volatility news from the previous period can explain current volatility. There is a significant negative result for the EGARCH model's asymmetric (leverage) term. As a result, negative shocks (bad news) have greater impact as compare to positive shock (good news) or day-of-the-week effect have a pattern of day-of-the-week effect impact on volatility, (Farag, 2013). The variance on Monday shows a positive significance in SSE, JALSH, MOEX and BSE. This implies higher volatility in Monday. A drop-in volatility was found to be significant in the next day in SSE, BSVP and BSE. The result of the finding claimed that estimate volatility will decrease in SSE, JALSH, and MOEX. However, an increase in volatility was found to be significant in BSE and IBOVESPA stock on Friday. The estimate result show that day-of-the-week effect on conditional variance is highest in SSE on Monday and lowest in BSE on Tuesday.

Furthermore, the volatility model with GED estimation in both analyses was less than 2 (GED < 2) in all windows. It means that the normal distributions of stock returns under fat tails should be considered under this condition. Consequently, we reject the null hypothesis that the residuals are linearly uncorrelated and homoscedastic as per the result of the Ljung-box Q (10) and Ljung-Box Q^2 (10) for serial correlation. For both GARCH and EGARCH models, the ARCH LM for heteroscedasticity is both insignificant and does not show any statistical significance. As a result, we can conclude that the model as a whole is well specified.

4.4.2. Day-of-the-week effect for G5 markets

Table 4.4 represents the result of the estimated equation for day-of-the-week effect (DOW) in the G5 countries. The Monday effect was found to be significant in

CAC 40 and FTSE counties at 10 percent level of significant. This result supports the earlier finding that Monday returns are higher than Friday returns. Tuesday returns have a significant negative effect on the S&P 500 (-0.031). The Tuesday return is positive in all countries except DAX 40 and S&P 500 and significant. No significant Wednesday effect was found in the developed market, similar that to in the emerging market. The return on Thursday shows a negative return in FTSE 100 (-0.036) at 10 percent. The Friday return shows a significantly positive return in FTSE 100 at the 5 percent level. Overall, the developed market shows no significant DOW effect compared with that of the emerging market. The results of our findings in developed markets also contradict the higher Fridays return than on any other day of the week and the lower return on Monday (Cross, 1973; Fama, 1980; Jaffe & Westerfield,1985).

Panel B of Table 4.4, represents the estimated result of the variance equation using GARCH and EGARCH. In both models, the ARCH effect was found to have a positive significance. This implies that return of a particular day are affected by the previous price movement of the stock. Higher return in t-day resulting in higher return in the subsequent day t+1. The GARCH and EGARCH models indicate that the US stock market experiences the highest persistent volatility (0.889, 0.979) and the French stock market has the lowest volatility (0.890, 0.979). A significant ARCH and GARCH coefficient indicate that volatility news from the previous period can explain current volatility. There is a significant negative result for the asymmetric (leverage) term of the EGARCH model. Consequently, negative shocks (bad news) have a lower impact than positive shocks (good news), or there is a pattern of DOW impact on volatility (Farag,2013). The variance on Monday is significantly positive in DAX40 and NIKKEI. This implies higher volatility in Monday. A significant negative Monday effect was found in the FTSE100 and S &P 500 stock markets. A significant drop in volatility was found on the next day in the CAC30, DAX40, and NIKKEI stock markets. The Thursday effect shows an increase in volatility in the CAC30, NIKKEI, and S&P500. A significant positive Friday was found to be significant in NIKKEI stock. The estimate result shows DOW on conditional variance is high on Friday as compared to that of Monday. Furthermore, the volatility model with GED estimation in both analyses was less than 2 (GED < 2) in all windows. It means that the normal distributions of stock returns under fat tails should be considered under this condition. Consequently, we reject the null hypothesis that the residuals are linearly uncorrelated and homoscedastic as a result of the Ljung-box Q (10) and Ljung-Box Q^2 (10) for serial correlation. For both GARCH and EGARCH models, the ARCH LM for heteroscedasticity is both insignificant and does not show any statistical significance. As a result, we can conclude that the model as a whole is well specified.

Table 4.3: Day-of-the-week effect in BRICS countries

	SSEC		IBOVESPA		JALSH		MOEX		SENSEX	
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
Panel A: Mean equation										
ω	0.171**	0.172**	0.002	1.589**	0.031**	0.163**	0.300	0.290**	0.202**	0.240**
MON	0.069**	0.078*	0.024**	-0.196*	0.073*	0.077*	0.114*	0.125*	0.030	0.026
TUE	0.100*	0.103*	0.090**	0.191**	-0.015	-0.019	-0.013	-0.021	-0.011	-0.011
WED	-0.242	-0.208	0.032	0.059	-0.022	-0.029	-0.007	-0.011	-0.029	-0.200
THU	-0.127	-0.136	-0.027	-0.064	0.010	0.013	-0.065	-0.063***	-0.004	-0.009
FRI	0.016	0.017	0.107**	-0.003	-0.046**	-0.036	-0.024	-0.022	0.015	0.012
Panel B: Conditional Variance Equation										
ω	-0.012*	2.183*	0.037*	4.681*	0.019*	-0.362*	0.031*	-0.155*	0.022*	0.066*
α	0.099*	0.208*	0.151*	0.243*	0.094*	0.168*	0.112*	0.217*	0.102*	0.218*
β	0.892*	-0.983*	0.550*	-0.884*	0.0893*	-0.978*	0.881*	0.988*	0.892*	-0.982*
γ		-0.031*		-0.168*		-0.084*		-0.039*		-0.051*
MON	0.378*	0.427*	-0.120*	-0.046**	-0.025	0.019**	0.058	0.128**	0.076	0.077**
TUE	-0.388*	0.427*	-0.294*	0.034	0.101**	0.047	0.182**	0.115**	-0.300*	-0.490*
WED	-0.304*	-0.247*	-0.035**	-0.240*	0.105**	0.149**	0.007	-0.062	-0.065	-0.041
THU	-0.049*	-0.279*	-1.078*	0.034	-0.016	-0.027	-0.064	0.115**	0.148**	0.123**
FRI	0.228*	-0.681	0.102**	-0.018	-0.195*	-0.179*	-0.065**	0.062	0.115**	0.126**
GED	1.073	1.001	1.239	1.378	1.434	1.476	1.28	1.282	1.435	1.459
Panel C: Model Diagnostic										
LLR	13985.36	13674.11	17263.31	17154.27	10108.97	100048.53	12054.26	12046.05	13341.83	13320.90
ARCH-LM	0.010	0.005	0.001	0.004	0.036	1.694	0.136	0.892	0.782	0.371
Q (10)	12.010	10.129	0.240	2.5303	0.023	30.281	0.136	27.881	0.783	87.597
$Q^2(10)$	1.089	47.531	0.246	53.767	21.140	33.398	8.045	30.169	2.094	96.051

Source: *Author's computation Using EViews*

Note(s): The table represent the result of the DOW effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q (10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, $Q^2(10)$ =Box-pierce Q^2 statistics for serial correlation at the 5 percent level of the order 10 lag,

Table 4.4: Day-of-the-week effect in G5 countries

	CAC 40		DAX 30		FTSE 100		NIKKEI 225		S&P 500	
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
Panel A: Mean equation										
ω	0.052**	0.019**	*0.077**	0.054**	*0.043**	0.024**	*0.038**	0.011**	*0.063**	*0.041**
MON	-0.043	-0.046**	0.017	0.004	-0.034**	-0.016	-0.008	-0.011	0.012	0.015
TUE	0.017	0.011	0.004	-0.001	0.026	0.017	0.011	0.019	-0.025	-0.031
WED	-0.010	-0.007	-0.027	-0.023	0.001	-0.007	-0.023	-0.032	0.014	0.023
THU	0.010	0.002	-0.010	-0.006	-0.036**	-0.035**	0.048	0.044	-0.016	-0.018
FRI	0.024	0.037	0.019	0.031	0.043**	0.045**	-0.017	-0.011	0.012	0.014
Panel B: Conditional Variance Equation										
ω	0.021**	-0.085*	0.059*	-0.109*	0.032*	-0.094*	0.014*	-0.131*	0.022*	-0.120*
α	0.094**	0.124**	0.090*	0.132*	0.092*	0.118*	0.098*	0.170*	0.102*	0.152*
β	0.890*	0.979**	0.899*	0.980*	0.890*	0.983*	0.884*	0.968*	0.889*	0.979*
γ		-0.108**		-0.093*		-0.101*		-0.103*		-0.129*
MON	-0.002	0.061	0.118*	0.157*	-0.075**	-0.012	0.149**	0.085*	-0.052**	-0.013**
TUE	-0.128*	-0.092***	-0.179*	-0.195*	0.067	0.027	-0.274**	-0.214*	0.010	0.044
WED	-0.063	-0.020	-0.114**	-0.076	0.012	-0.002	-0.069	-0.005	-0.018	-0.070
THU	0.117**	0.046	0.056	0.046	-0.005	0.034	0.098	0.122**	0.063**	0.086**
FRI	0.034	-0.031	0.115**	0.032	-0.017	-0.055	0.200*	0.127*	0.027	0.010
GED	1.451	1.483	1.372	1.4	1.39	1.43	1.39	1.442	1.31	1.35
Panel C: Model Diagnostic										
LLR	13170	13049	13157.48	13072.28	11073.	10976.	13728.19	13635.10	10876.63	10762.23
ARCH-LM	2.15	0.45	2.27	1.271	0.006	0.005	1.066	0.019	0.075	0.148
Q(10)	12.87	15.52	6.47	7.31	9.62	9.75	3.16	2.94	5.88	15.98
$Q^2(10)$	12.53	7.07	5.537	3.387	12.425	15.407	5.29	6.11	14.52	10.71

Source: *Author's computation Using EViews*

Note(s): The table represent the result of the DOW effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q (10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, $Q^2(10)$ =Box-pierce Q^2 statistics for serial correlation at the 5 percent level of the order 10 lag,

4.4.3 Month of the year effect

Table 4.5 represents the results of the month of the year effect and January effect for the Chinese stock market. The estimated results for other markets are presented in Appendix II and Tables 3 and Table 4. Table 4.6 depicts the summary of the month of the year and January effect for all return series. The results of the mean return indicate that the January effect is positive and statistically significant in SSE. This indicates that a January effect exists in the Chinese market. In contrast, such a January effect was not found to be significant in other studies. The February effect shows a positive significant mean return in SSE and CAC30. A significant negative mean return in March was found in JALSH. April effect shows a positive and significant mean return in CAC30 and FTSE100 at 5 percent and 10 percent respectively. No significant May effect was found in any of the countries, except CAC30 at the 10 percent level. The emerging market shows no June anomaly; however, the developing market shows a negative June anomaly in CAC 30, FTSE100, and S&P500 at the 5 percent level. A positive August anomaly was found in IBOVESPA, and a negative August anomaly in CAC30 and DAX40. The result shows a negative September mean return for JALSH, DAX40, and FTSE10, and a positive return for CAC30. A significant positive mean return on the FTSE 100 was found in November. Moreover, no July, October, or December anomalies were observed in any of the analysed months. The BSE and Nikkei show no anomaly over the entire period, which indicates that investors do not earn abnormal profits due to the month of the year effect. Overall, the results suggest that the frequency of the MOY effect is higher in developed countries than that in emerging countries. No evidence of the January effect is observed, as the mean return is statistically different from zero, except for the Chinese stock market.

Panel B of Table 4.5 and Table 4.6 represent the results of the conditional variance equation. The volatility of returns in January on the IBOVEPSPA, BSE, FTSE100, and S&P500 are positive and statistically significant. In IBOVESPA, BSE and MOEX markets, the return volatility on February was positive and significant in IBOVESPA, BSE and MOEX market at 1 percent and 5 percent. A negative March anomaly with lower volatility was found in SSE at 10 percent whereas the IBOVESPA and Nikkei Stock had a positive anomaly with increased volatility of 5% and 1%, respectively. However, the opposite effect was observed in the next month of April and May. A significant negative volatility was found in MOEX and BSE market in June. It is also observed that lower(negative) volatility was found to be significant in July, August, December for the IBOVESPA market at the one percent level, JALSH and S&P 500 in July, and FTSE 100 in December. The increase in volatility of returns was found to be significant in SSE at the 1 percent level in October and November, IBOVESPA in September, and IBOVESPA, BSE, and FTSE100 in September at the 5 percent level of significance. There is no discernible volatility trend across markets. In contrast to the return equation, emerging markets exhibit higher return volatility than developed countries It indicating that the model used to test the month of the year effect is linearly uncorrelated and homoscedastic as given by the Ljung-box Q (10) and Ljung-Box Q2 (10) results for autocorrection derived from the residual diagnostic, which show the model is fitted well. The model is also free from ARCH LM for the heteroscedasticity problem.

Table 4.5: Month of the year effect in Chinese stock exchange

	January		February		March		April		May		June	
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
Panel A: Mean equation												
ω	0.047	0.047*	0.050	0.047*	0.054	0.052	0.055	0.055	0.055	0.054	0.051	0.051
SSE	0.082**	0.082**	0.064	0.136*	-0.036	-0.008	-0.026	-0.039	-0.037	-0.038	0.000	0.000
Panel B: Conditional variance equation												
ω	0.038*	-0.125*	0.037*	-0.036*	0.040*	-0.124*	0.037*	-0.125*	0.038*	-0.130*	0.039	-0.124
α	0.113*	0.196*	0.114*	0.054*	0.112*	0.197*	0.112*	0.194*	0.113*	0.200*	0.113*	0.196*
β	0.885*	0.984*	0.884*	0.984*	0.885*	0.984*	0.885*	0.985*	0.884*	0.984*	0.884*	0.984*
γ		-0.023*		-0.023*		-0.023*		-0.023		-0.023*		-0.023*
SSE	0.001	0.005	0.021	0.004	-0.020	-0.015	0.025	0.020*	0.014	0.032*	0.002	-0.011
Panel C: Diagnostic												
GED	1.003	0.986	1.008	0.991	1.005	0.987	1.005	0.988	1.004	0.994	1.004	0.988
LLR	-13997.46	-13980.66	-13997.81	-13980.21	-13997.88	-13980.73	-13997.49	-13979.68	-13998.34	-13976.19	-13998.89	-13981.44
LM- ARCH	0.014	0.001	0.016	0.000	0.013	0.001	0.013	0.001	0.013	0.013	0.014	0.001
Q(10)	0.306	0.037	0.132	0.302	0.135	0.299	0.317	0.126	1.425	1.431	1.443	0.182
Q2(10)	0.819	0.756	0.764	0.773	0.587	0.607	0.113	1.611	0.389	0.382	0.389	8.427
Month of the year effect in Chinese stock exchange (Continued)												
	July		August		September		October		November		December	
Panel A: Mean equation												
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
ω	0.051*	0.051*	0.050*	0.051*	0.056*	0.055*	0.051*	0.051*	0.047*	0.047*	0.050*	0.050*
SSE	-0.010	0.014	0.008	-0.015	-0.049	-0.047	0.004	0.000	0.048	0.029	0.028	0.017
Panel B: Conditional variance equation												
ω	0.040*	-0.124*	0.040*	-0.123*	0.039*	-0.125*	0.040*	-0.125*	0.039*	-0.124*	0.038*	-0.125*
α	0.113*	0.196*	0.113*	0.195*	0.113*	0.196*	0.113*	0.196*	0.113*	0.196*	0.113*	0.196*
β	0.884*	0.984*	0.885*	0.984*	0.885*	0.984*	0.884*	0.984*	0.885*	0.984*	0.885*	0.984*
γ		-0.023*		-0.023*		-0.023*		-0.023*		-0.023*		-0.023*
SSE	-0.009	-0.006	-0.014	-0.012	-0.004	-0.004	-0.011	-0.003	-0.005	-0.009	0.010	0.001
Panel C: Diagnostic												

GED	1.001	0.987	1.004	0.988	1.005	0.988	1.001	0.987	1.004	0.988	1.004	0.987
LLR	-13998.71	-13981.91	-13998.42	-13981.18	-13997.96	-13981.25	-13998.71	-13982.08	-13998.33	-13981.34	-13998.59	-13982.02
LM- ARCH	0.014	0.001	0.014	0.001	0.014	0.001	0.014	0.014	0.014	0.001	0.013	0.001
Q(10)	1.611	1.441	0.466	0.084	0.313	0.636	0.225	0.108	0.709	0.251	0.262	0.741
Q2(10)	8.757	9.243	0.301	0.136	0.135	0.302	0.304	0.135	0.304	0.135	0.303	0.302

Source: *Author's computation Using EViews*

Note(s): The table represent the result of the MOY effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively.

GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q(10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, $Q^2(10)$ =Box-pierce Q^2 statistics for serial correlation at the 5 percent level of the order 10 lag,

Table 4.6: Month of the year effect for all return of the stock markets

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Panel A: Mean Equation												
SSE	Yes, 5%	Yes, 5%	No	No	No	No	No	No	No	No	No	No
IBOVESPA	No	No	No	No	No	No	No	No	No	No	No	No
JALSH	No	No	No	No	No	No	No	No	No	No	No	No
MOEX	No	No	No	No	No	No	No	No	No	No	No	No
BSE	No	No	No	No	No	No	No	No	No	No	No	No
CAC	No	Yes, 5%	No	Yes, 5%	Yes, 10%	**Yes, 5%**	No	**Yes, 10%**	Yes, 1%	No	No	No
DAX	No	No	No	No	No	No	No	**Yes, 1%**	**Yes, 1%**	No	No	No
FTSE 100	No	No	No	Yes, 10%	No	**Yes, 5 %**	No	No	**Yes, 5%**	No	No	No
NIKKEI	No	No	No	No	No	No	No	No	No	No	No	No
S&P 500	No	No	No	No	No	**Yes, 5 %**	No	No	No	No	Yes, 5 %	No
Panel B: Variance Equation												
SSE	No	No	**Yes, 10%**	Yes, 5 %	Yes, 1 %	No	No	No	No	Yes, 1 %	Yes, 1%	No
IBOVESPA	Yes, 1 %	Yes, 5 %	Yes, 1%	**Yes, 1%**	**Yes, 1%**	No	**Yes, 1%**	**Yes, 1%**	No	Yes, 1%	No	**Yes, 1%**
JALSH	No	No	No	No	No	No	**Yes, 10%**	No	No	No	No	No
MOEX	No	Yes, 1 %	No	No	No	**Yes, 5%**	No	No	Yes, 5%	No	No	No
BSE	Yes, 5%	Yes, 1 %	No	No	No	**Yes, 5%**	Yes, 1 %	No	Yes, 5%	No	No	No
CAC	No	No	No	No	No	No	No	No	No	No	No	No
DAX	No	No	No	No	No	No	No	No	No	No	No	No
FTSE 100	Yes, 1%	No	No	No	No	No	No	No	Yes, 5%	No	No	**Yes, 5%**
NIKKEI	No	No	Yes, 5%	Yes, 5%	**Yes, 5%**	No	No	No	No	No	No	No
S&P 500	Yes, 1%	No	No	No	No	No	**Yes, 5%**	No	No	No	No	No

Source: *Author's computation Using EViews*

Note(s): Bold represent positive coefficient. The table represent the result of the MOY effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q(10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, Q2(10) =Box-pierce Q2 statistics for serial correlation at the 5 percent level of the order 10 lag,

4.4.4 Turn of the Month effect for BRICS markets

Table 4.7 presents the estimated TOM effect results utilising GARCH and EGARCH models for BRICS markets. The mean equation in Panel A displays the coefficients of the variables representing the turn of the month effect. Ariel's (1987) TOM was found to be statistically significant for the JALSH and BSE stock market indices. However, the result was contrary in the BSVP stock market, as a negative return (-0.040) was found to be significant at the 1 percent level. The TOM of Lakonishok and Smidt (1988) was significant in JALSH and IBOVESPA at the 5 percent and 10 percent levels, respectively. TOM [-5, +1] exhibits a negative significant return in the SSE and a positive significant return in the BSE market. TOM [-1, +5] provides evidence of significantly higher returns in the IBOVESPA, SSE, and MOEX markets. For the SSE (China) and BSE (India), the evidence is mixed. The GARCH models demonstrate significant positive coefficients on TOM [-5, +1] or TOM [-1, +5], whereas the EGARCH models show less evidence of this effect. It is evident that there is a presence of the turn of the month effect in the BRICS countries. The results provide evidence of a turn of the month effect in Brazil and Russia, some weak evidence in China and India, and limited evidence in South Africa. The effect appears more pronounced around month-beginnings than around endings.

The variance equation in Panel B of Table 4.7 shows the ARCH effects α are positively significant across both models, implying that returns on a given day are influenced by prior price movements. Higher returns on day *t* predict higher returns on the subsequent day t+1. The volatility persistence measured by the GARCH term proves significant and positive at the 1 percent level. Among BRICS countries, volatility persistence appears most pronounced for India's BSE (0.894, 0.981) under the GARCH and EGARCH specifications respectively, while Brazil's IBOVESPA demonstrates the lowest persistence (0.792, 0.963). The significance of both the ARCH and GARCH coefficients indicates that current volatility incorporates new information, as well as residual effects from previous periods. However, the asymmetric or leverage parameter exhibits a negative significance under the EGARCH formulation. Accordingly, bad news in the form of negative shocks or disturbances has less impact than good news or positive shocks, a finding which repudiates the typical leverage effect. This implies the day-of-the-week effect does not uniformly intensify volatility, whether it is good or bad. Instead, the results suggest that volatility responds asymmetrically, with negative returns or “bad” days mitigating subsequent uncertainty less than positive returns or “good” days, ceteris paribus. The volatility in Ariel (1987) TOM shows insignificance in most of the markets except for IBOVESPA and BSE. A significant positive TOM was found in IBOVESPA and JALSH, and lower volatility in BSE under Lakonishok and Smidt (1988) estimation. Higher volatility in the last five trading days and first trading days was found to be significant in the SSE, MOEX, and BSE markets, and lower volatility was found in the JALSH market. No significant volatility persistence was found in the initial month TOM [-1, +5], except for IBOVESPA, and the return volatility was significantly lower in the IBOVESPA market. In summary, the results show that turn-of-month volatility effects are more pronounced for India and China, while Brazil shows lower volatility around month turns. The results of (Ariel, 1987; Lakonishok & Smidt, 1988) estimation provides no additional explanatory power. With all residual diagnostics being insignificant, the models can be considered well-specified and provide a good fit for volatility processes in the BRICS markets. The results and inferences are valid based on these diagnostics and no model misspecification.

4.4.5 Turn of the Month effect for G5 markets

The estimated result of the TOM effect from the GARCH and EGARCH models of the G5 countries is shown in Table 4.8. The mean equation in Panel A shows the coefficients of the variables representing the turn of the month effect. The Ariel (1987) TOM effect was found to be insignificant in the analysed stock market, except for Nikkei. Lakonishok and Smidt (1988) show significantly higher returns on the FTSE 100 stock market. TOM [-5, +1] shows positive returns in the CAC30 and DAX 40 markets. TOM [-1, +5] provides no evidence of a significantly higher return, but a negative return is found in the S&P 500 market. Overall, the results show that a significant TOM effect for the French and German stock markets leads to higher returns, specifically during the turn of the month.

The result of the variance equation is shown in Panel B of Table 4.8. The ARCH effects α are significantly positive in both models, implying that returns on a given day are influenced by prior price movements. Higher returns on day *t* predict higher returns on the subsequent day t+1. The volatility persistence measured by the GARCH term proves significant and positive at the 1 percent level. The significance of both the ARCH and GARCH coefficients indicates that current volatility incorporates new information, as well as residual effects from previous periods. However, the asymmetric or leverage parameter exhibits a negative significance under the EGARCH formulation. This implies the DOW effect does not uniformly intensify volatility, whether good or bad. Instead, the results suggest volatility responds asymmetrically, with negative returns or "bad" days mitigating subsequent uncertainty less than positive returns or "good" days. The volatility in Ariel (1987) shows that TOM is insignificant in most markets, except for Nikkei. A significant positive TOM (Lakonishok & Smidt, 1988) was found in the FTSE 100 at 5 percent and 10 percent. No significant volatility persistence was found in the initial month TOM [-1, +5, +1, -5], except for FTSE and CAC30. In summary, only FTSE100 shows some volatility effects related to turn-of-the-month trading. Nikkei exhibits higher volatility around the end of the month. Otherwise, developed markets do not demonstrate strong monthly volatility patterns tied to TOM calendar anomalies. With all residual diagnostics being insignificant, the models can be considered well-specified and provide a good fit for volatility processes in the BRICS markets. The results and inferences are valid based on these diagnostics and no model misspecification.

Table 4.7: Turn of the month effect in BRICS countries

	SSEC		IBOVESPA		JALSH		MOEX		SENSEX	
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
Panel A:Mean equation										
ω	0.009	0.009	0.022	0.040	0.024	0.230	0.031	0.014	0.027	-0.007
Ariel (1987)	0.036	0.035	-0.014	-0.040*	0.061**	0.057**	-0.007	-0.005	0.050***	0.062**
LS (1988)	0.068**	0.086**	0.079**	0.000	0.014	0.008	0.007	0.011	0.032	0.038
ToM_1	-0.055***	-0.071**	-0.001	0.000	-0.004	0.006	0.062	0.068	0.065	0.076**
ToM_2	0.073**	0.064**	0.128*	0.000	0.039	0.041	0.169**	0.167*	0.017	-0.001
Panel B: Variance Equation										
ω	0.011*	-0.124*	0.301*	-0.036*	0.016*	-0.138*	-0.003*	-0.161*	0.020*	-0.180*
α	0.115*	0.202*	0.183*	0.077*	0.096*	0.166*	0.112*	0.212*	0.102*	0.216*
β	0.883*	0.984*	0.792*	0.863*	0.892*	0.979*	0.887*	0.989*	0.892*	0.981*
γ		-0.024*		-0.056*		-0.084*		-0.039*		-0.050*
Ariel (1987)	0.046	-0.021	-0.138	0.040**	-0.001	0.017	-0.008	-0.007	-0.009	0.035***
LS (1988)	-0.269**	-0.279*	1.034*	-0.069	0.115**	0.123***	-0.133	-0.037	-0.192**	-0.215*
ToM_1	0.227**	0.193*	0.746*	0.161**	-0.082**	-0.074	0.174**	0.067	0.171*	0.221*
ToM_2	0.095	0.155*	-0.352**	-0.030	-0.037	-0.063	0.120	0.036	0.082	0.045
GED	1.009	1.095	1.007	1.120	1.439	1.074	1.297	1.328	1.443	1.449
Panel C: Model Diagnostic										
LLR	3978.75	13959.11	15795.48	16189.65	10093.37	10038.69	12029.94	12029.71	13328.39	13426.14
ARCH-LM	0.015	0.002	0.008	0.000	0.035	0.069	0.141	0.772	0.705	0.806
Q (10)	0.100	0.063	20.564	0.059	1.448	2.064	30.563	30.636	2.297	4.022
$Q^2(10)$	0.323	0.185	0.317	0.656	28.153	22.064	11.069	13.155	7.157	12.159

Source: *Author's computation Using EViews*

Note(s): The table represent the result of the TOM effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. ToM_1= (-1,+5) and ToM_2 = (-5, +1). GED= Generalised error distribution estimated using Eview Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q(10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, $Q^2(10)$ =Box-pierce Q^2 statistics for serial correlation at the 5 percent level of the order 10 lag,

Table 4.8: Turn of the month effect in G5 countries

	CAC30		DAX40		FTSE100		NIKKEI		S&P500	
	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH	GARCH	EGARCH
Panel A:Mean equation										
ω	0.012	-0.019	0.054**	0.028***	0.033**	0.011**	0.024	-0.007	0.047**	0.025**
Ariel (1987)	0.002	0.009	0.010	0.014	-0.030	-0.027	0.003	-0.001	0.031	0.034***
LS (1988)	-0.022*	-0.014	-0.010	-0.011	0.068**	0.063**	0.030	0.035	0.024	0.022
ToM_1	0.111**	0.109*	0.049	0.056**	-0.036	-0.028	0.026	0.033	0.014	0.015
ToM_2	0.075	0.052	0.045	0.037	0.044	0.038	-0.022	-0.019	-0.033	-0.040***
Panel B: Variance Equation										
ω	0.031*	-0.090*	0.042*	-0.083*	0.020*	-0.105*	0.001	-0.143*	0.011*	-0.130*
α	0.096*	0.125*	0.091*	0.133*	0.095*	0.122*	0.097	0.168*	0.102*	0.152*
β	0.891*	0.980*	0.898*	0.981*	0.888*	0.983*	0.886	0.969*	0.890*	0.979*
γ		-0.109*		-0.094*		-0.102*		-0.104*		-0.129*
Ariel (1987)	-0.004	-0.002	-0.047	-0.038	-0.008	0.019	0.069	0.049**	-0.001	0.010
LS (1988)	0.072	0.053	-0.028	-0.025	0.118**	0.189*	0.002	-0.049	0.020	0.072
ToM_1	-0.014	-0.005	0.013	0.016	-0.079**	-0.107**	0.062	0.079	-0.010	-0.034
ToM_2	-0.073**	-0.058	0.032	0.024	-0.050**	-0.122*	-0.051	-0.011	-0.004	-0.042
GED	1.449	1.483	1.372	1.403	1.399	1.431	1.382	1.431	1.307	1.356
Panel C: Model Diagnostic										
LLR	13153.71	13033.07	13154.03	13071	11060.83	10962.11	13729.11	13628.85	10874.34	10758.27
ARCH	1.726	0.481	1.906	1.359	0.008	0.003	1.239	0.002	0.083	0.176
Q(10)	13.009	0.132	6.443	7.228	8.427	8.570	3.596	3.208	18.718	17.156
$Q^2(10)$	13.286	12.694	5.398	3.269	11.767	15.068	5.336	5.413	15.042	10.588

Source: *Author's computation Using EViews*

Note(s): The table represents the estimate result of the TOM effect on both return and conditional variance using GARCH and EGARCH estimation. *, **, ***, indicate significance at the 1%, 5% and 10% level respectively. ω, α ,β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. ToM_1= (-1, +5) and ToM_2 = (-5, +1). GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q (10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, $Q^2(10)$ =Box-pierce Q^2 statistics for serial correlation at the 5 percent level of the order 10 lag,

4.5 Time varying calendar anomalies

The presence of adaptive market behaviour in the calendar offers an opportunity for abnormal gains from time to time. Initial examination of calendar anomalies using the complete dataset did not provide conclusive evidence. Therefore, it is essential to conduct a more in-depth analysis to gain a better understanding of the patterns and characteristics of these anomalies. This involves breaking down the data into smaller subsets or periods, enabling a more granular investigation of calendar effects across different timeframes or market conditions. For this, a fixed window of 3 years behaviour of the stock return was analysed. GARCH (1,1) is primarily estimated in this window framework to explore the time-varying pattern of the calendar effect and set of data points to understand how the anomalies have behaved over time. The three-yearly subsamples are chosen to provide sufficient observation to obtain a reliable result; a minimum of 500 to 1000 observations is often recommended. This three-year daily data provides a required observation; additionally, model diagnostic and model evaluation provide adequacy in model fit with the sample size used.

4.5.1 Time varying Day-of-the-week effect in BRICS market

The results for the DOW effect on the BRICS market are shown in Figure 4.1. The linear line in the figure represents a significant level of 10 percent. The result for the DOW effect on SSE market in Figure 4.1(a) and 4.1(b) revealed that excess return was negative until 2004, significant positive return was found until 2010 when excess return turned negative in 2011-2013. Thus, the Monday, Tuesday, and Wednesday returns behave in a switching manner in the SSE and are type 3. The Friday return seems to be positive and negative over the entire sample period, so the effect seems to be adaptive in nature and type 4. The Thursday effect shows a significant negative return over time, except for the period 2002-2004 which signifies market inefficiency and type 5. The SSE market indicates that anomalies still manifest in the market.

The results for the day-of-the-week effect for the SSE market are shown in Figures 4.1(c) and 4.1(d). The Monday effect in the JALSH market shows a switching nature and is classified as type 4 (adaptive nature). The market moved toward efficiency (Type 2) in 2010. The JALSH day-of-the-week effect provides a negative return, followed by a positive return, and the market moves toward efficiency (type 2). The Monday and Thursday effects are more pertinent than those on other days of the week.

The DOW effect for the BSE market represented in Figure 4.1(e) and 4.1(f) exhibits significant Monday and Friday market anomalies in the 1993-1995 period. The reverse is true in the 1999-2021 period when the market is inefficient. The market anomalies disappear over time, and the market moves toward efficiency (Type 2). Adaptive behaviour was found to behave before the global pandemic event and the market moved toward efficiency.

The DOW effect in IBOVSPA, shown in Figures 4.1(g) and 4.1(h), shows a significant weekday effect before 2007. Monday anomalies were found to be significant during 1993-1995 and 2002-2004 periods. Friday anomalies were found to be significant in the 1999-2021 and 2002-2004 period; the market is an anomaly switch (Type 3). The market anomalies disappear over time and the market is moving toward efficiency (Type 2) and The IBOVESPA indicates the existence of an adaptive market (Type 4).

The DOW effect for the MOEX market is exhibited in Figures 4.1(i) and 4.1(j), which show a market inefficiency over time and anomalies switch from a negative return followed by a positive return (type 5), indicating that anomalies in the market are still prevalent. A positive Monday return and negative Friday return were found to be significant (Type 3), and the calendar effect on Tuesday, Wednesday, and Thursday are more pertinent than the Monday and Friday effects on the return of the IBOVESPA index.

The emerging market shows significant market anomalies with excess returns in JALSH, MOEX, and SSE, and moves toward efficiency in BSE and IBOVESPA. This result is consistent with Lo (2012)

4.5.2 Time varying Day-of-the-week effect in G5 market

The result of the day-of-the-week effect for developing countries are depicted in Figure 4.2. The result for the DOW effect in the CAC40 in Figure 4.2(a) and 4.2(b) revealed negative excess return followed by positive return and market anomalies were found to be significant from the period between 2011-2016. The market experiences an adaptive market where the market can be classified as efficient and in efficient overtime under different sub-period. The Tuesday return behaves with a trend line turning negative and type 3. Wednesday returns show a market return move toward efficient (Type 2). Thursday and Friday returns show a period of efficiency and inefficient resulting in Type 3.

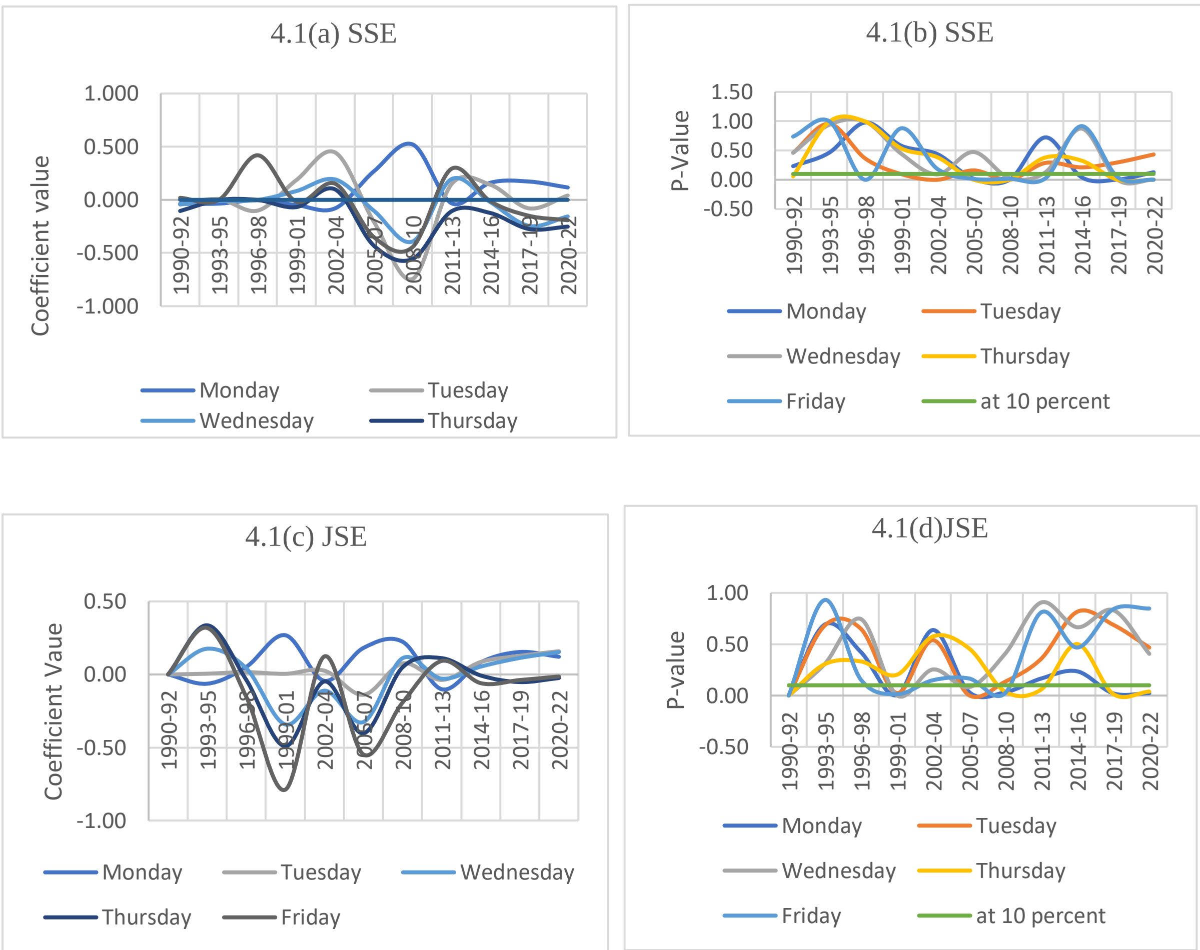
The DOW effect in DAX 30 depicted in Figure 4.2(c) and 4.2(d) shows a negative and lower return than most of the other days of the week. The Tuesday return provides a market that is efficient. No significant anomalies were found in the DAX 40 market except for a period 1999-2001 and 2008-2010. The Friday return shows the adaptive behaviour. Overall, the DAX 40 market is classified as type 5.

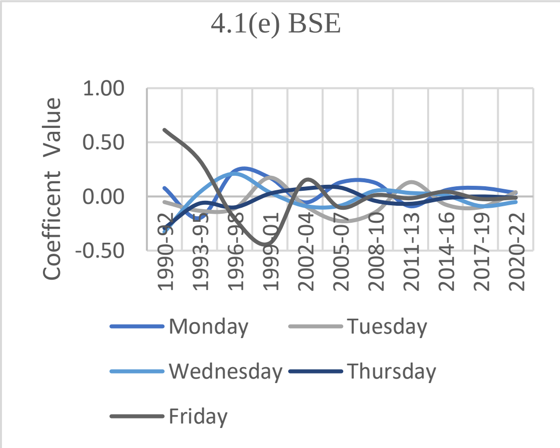
As shown in Figure 4.2(e) and 4.2(f), the DOW effect in FTSE 100 market exhibits significant Tuesday and Thursday return anomalies in the 1990-1992 period. The Friday anomalies were found in the 2005-2007 period and disappeared over time. The Monday anomalies were found in 2008-2010 and disappeared. The Thursday effect shows the market moving toward inefficient (Type 5). The day-of-the-week effect on Tuesday shows adaptive market behaviour (Type 4) and Monday, Wednesday and Thursday move toward efficient (Type 2).

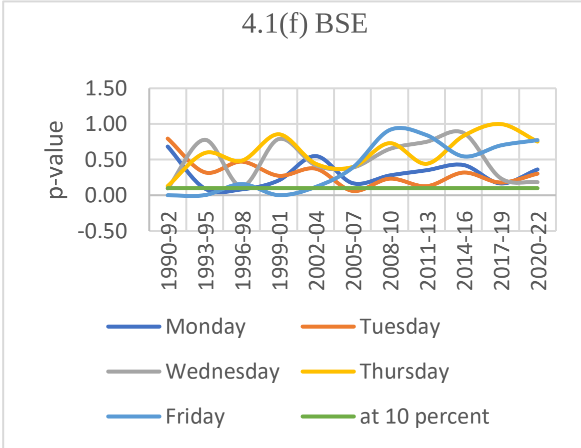
The DOW Effect for Nikkei 225 is represented in Figure 4.2(g) and 4.2(h) exhibits the Monday anomalies are found to be significant until 1998. However, the Monday effect disappeared afterward. Tuesday's effect shows adaptive behaviour till 2010 and the market moves toward efficiency. Wednesday and Thursday anomalies show the efficient market overtime and switch toward efficiency and The Friday anomalies were found to be significant only in the 1990-1992 period. The Nikkei 255 index exhibits a time varying return and market move toward efficiency after 2014.

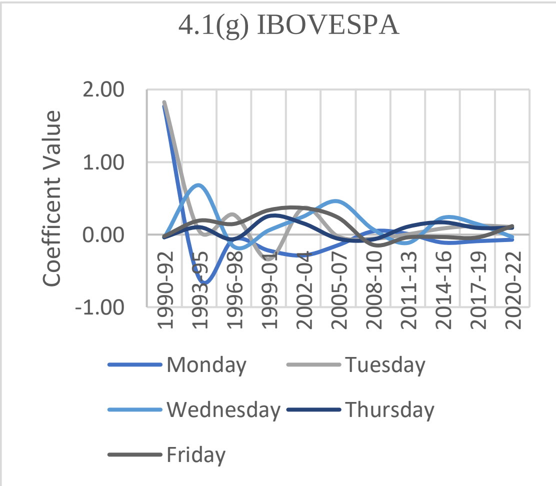
The result in Figure 4.2 (i) and 4.2(j) show the Monday effect in S&P 500 behaves in a positive significant return followed by excess return (Type 3). Tuesday's effect shows the market moves toward efficiency (Type 2). Wednesday shows the efficient market overtime (Type 1). Thursday and Friday effects show the efficient market overtime and switch toward efficiency (Type 4). The S&P 500 index exhibits no Monday anomaly and Friday anomaly was found to be significant overtime.

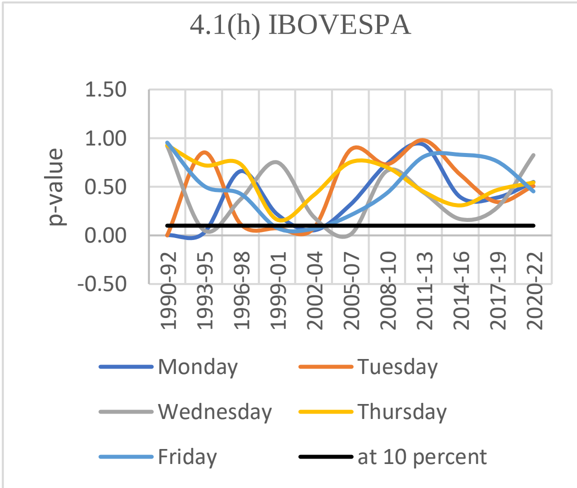
Figure 4.1: The three-year fixed window day-of-the-week effect estimated using GARCH (1,1) in BRICS markets

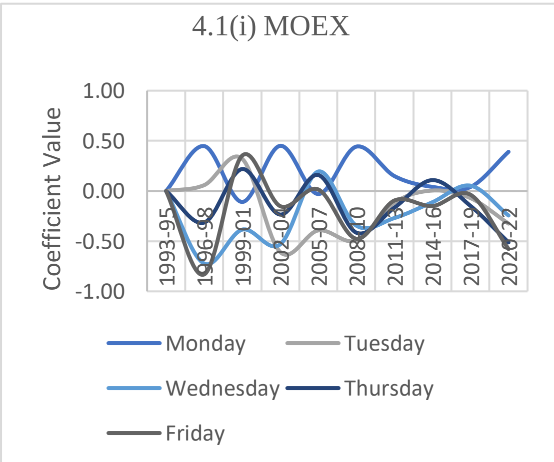


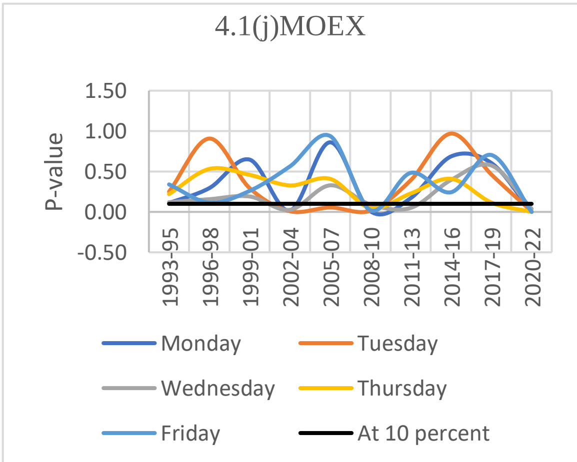






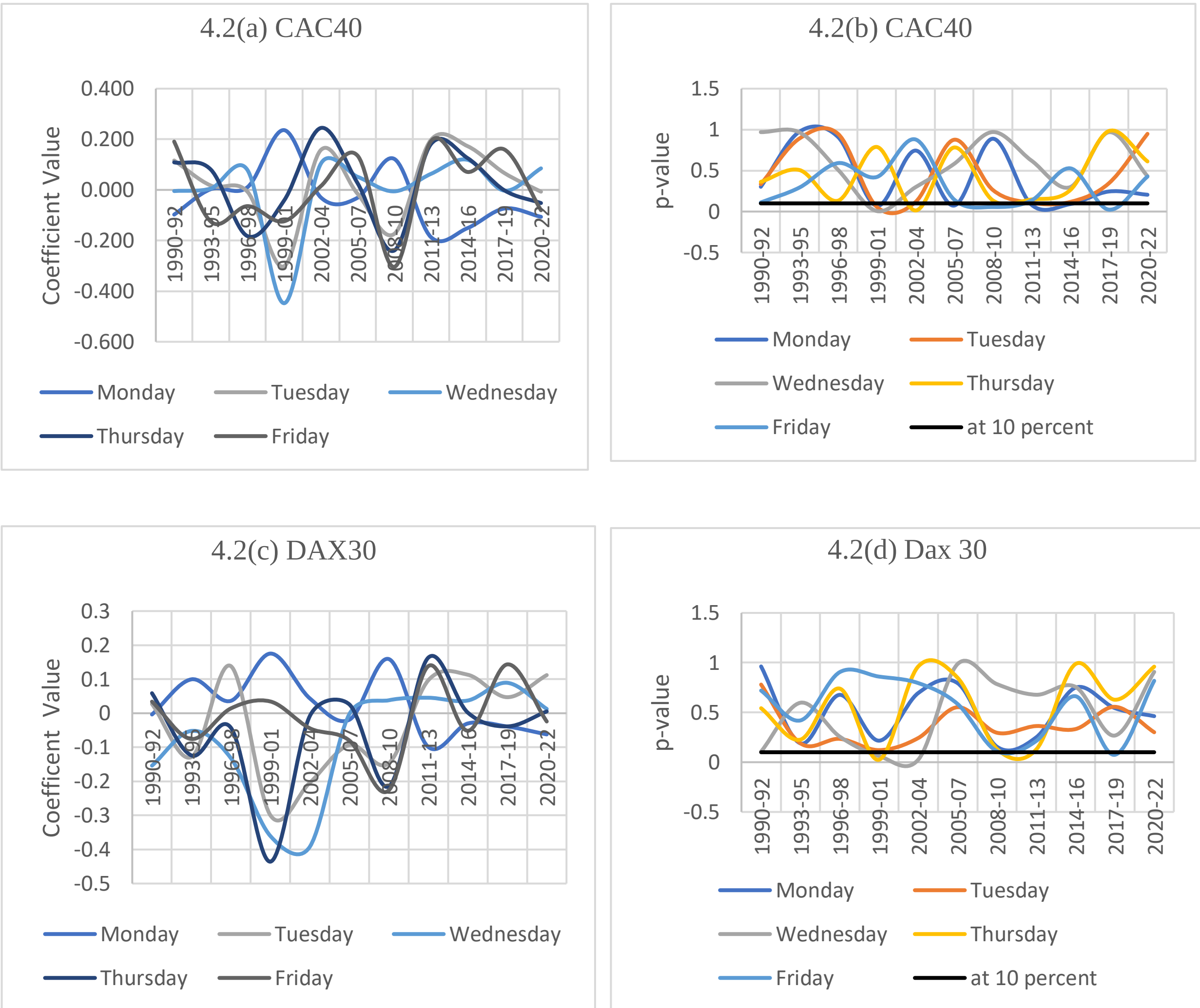


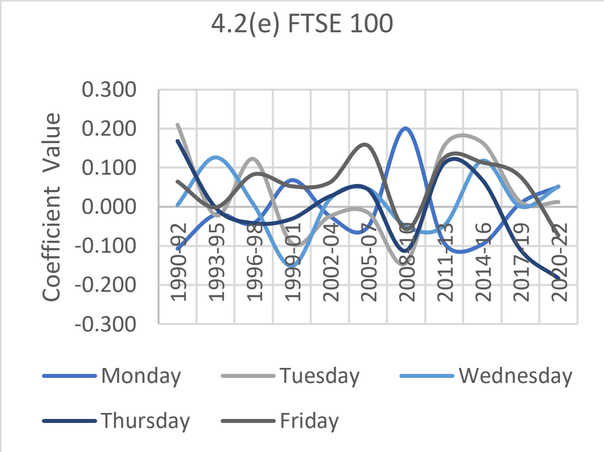


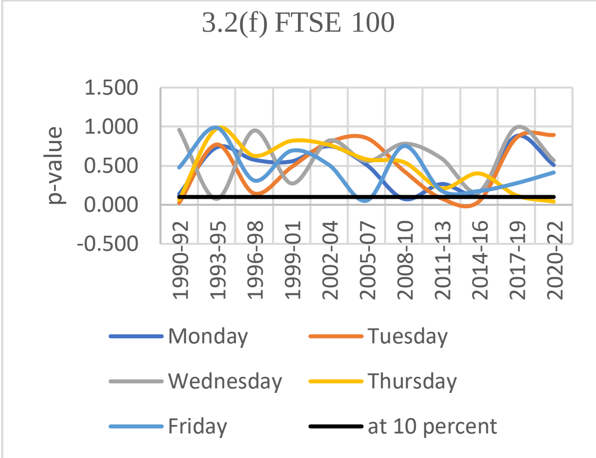


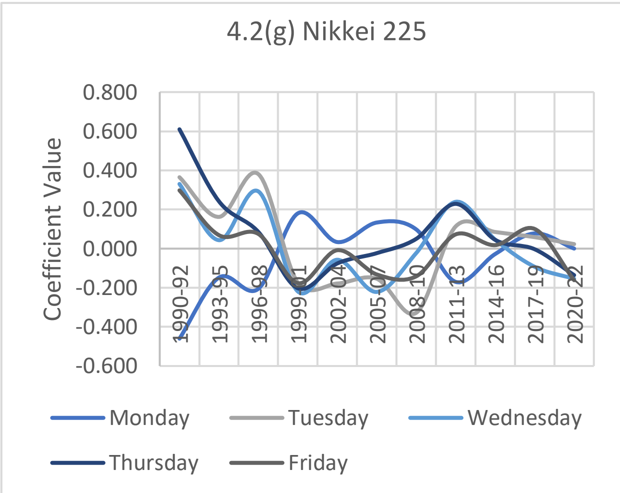
Source: Author's Computation

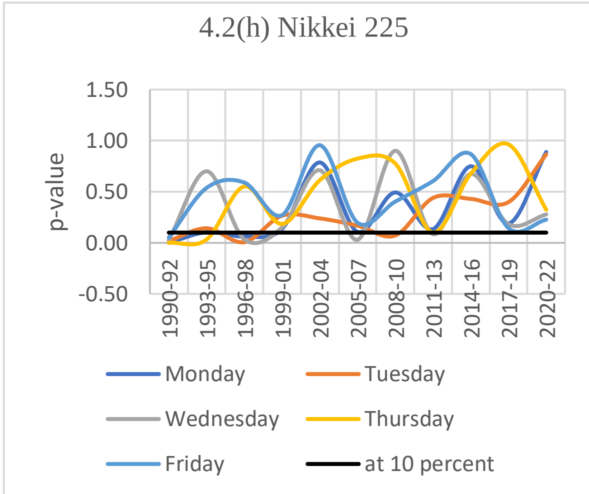
Figure 4.2: The three-year fixed window day-of-the-week effect estimated using GARCH (1,1) in G5 markets

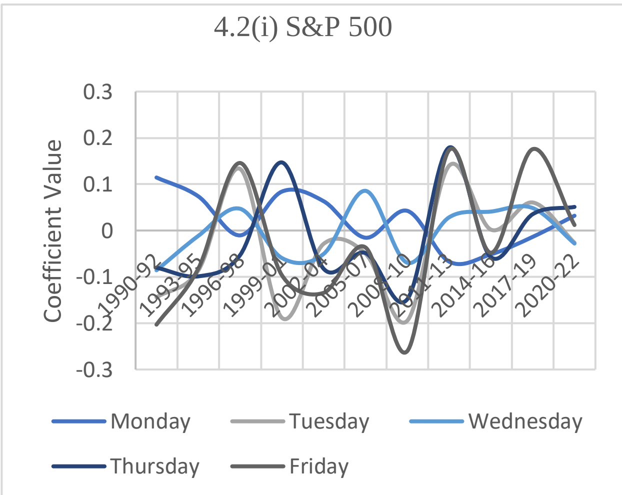


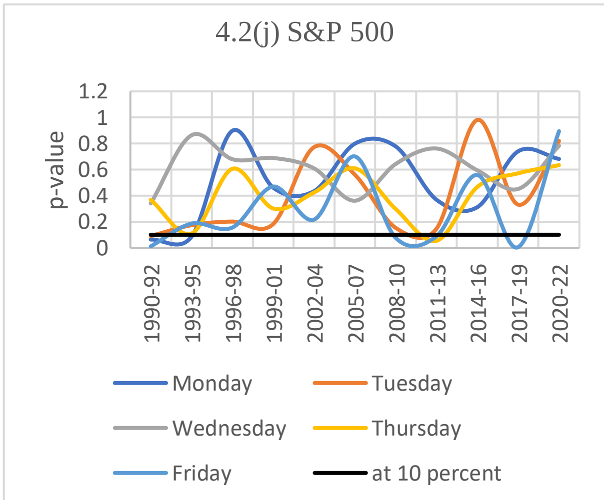












Source: Author's Computation

4.5.3. Time varying month of the Year effect

In this section, the return for month of the year effect for emerging and developed market are documented.

4.5.4 Time varying month of the year in BRICS market

The MOY Effect for Nikkei SSE is represented in Figure 4.3(a). The result show January effect was found to be significant during the period of 1990-1992, 1996-1998, 2002-2004, and 2014-2016. The return show fluctuation consistently appears overtime and the market can be classified as adaptive behaviour (Type 4). February effect appears to be significant on 1990-1992 and eventually disappears, thus the market is moving toward efficiency (Type 2). The march effect shows a perfect market efficiency (Type 1). A significant positive and negative coefficient return is observed in April, May, and June indicating the market behaviour be adaptive in nature (Type 4). July, August, and November effect show initial anomaly and the market move towards efficient (Type 2). October and December effect show a switch in the coefficient return overtime in the subsample period and deemed to be classified as type 3.

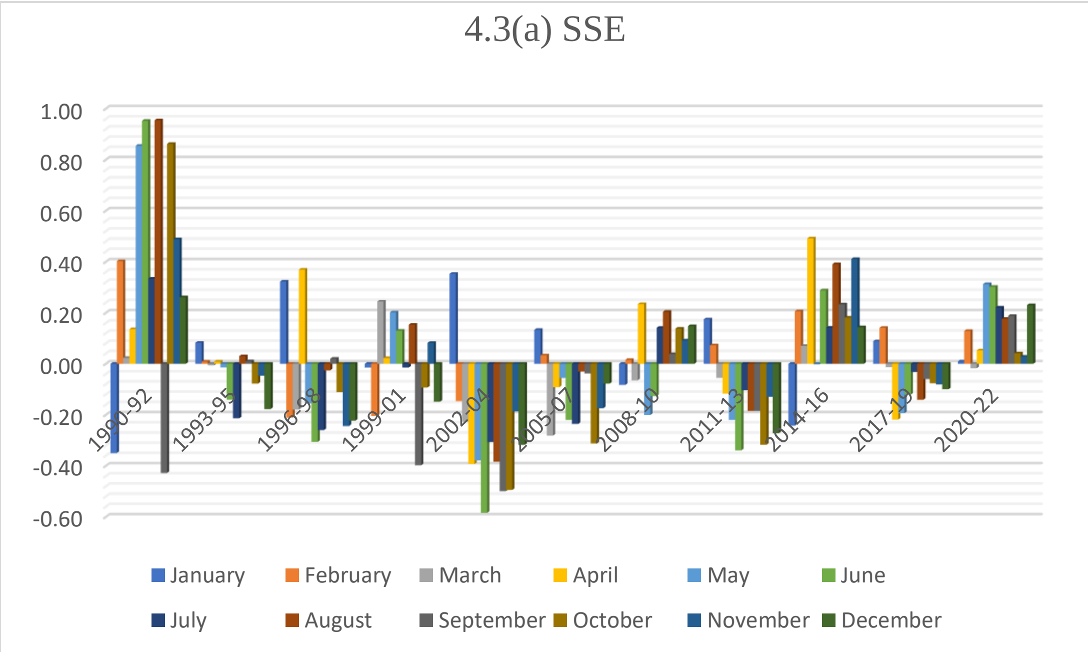
The estimated result of MOY Effect for JALSH is represented in Figure 4.3(b). The result show January and March effect was found to be significant negative and during the period of 2008-2010 respectively, implies the return in this period show the least and higher return respectively. The market can be classified as moving towards efficiency (Type 2). February and November effect appears to be significant during 1996-1998 and disappear, whereby the market is said to be moving toward efficient (Type 2). The July and September return show fluctuate consistently overtime and the market can be classified as adaptive behaviour (Type 4). The April and June effect show a perfect market efficient (Type 1). The JALSH market show a significant negative and positive excess return throughout the sample, the market can be defined as perfectly efficient in certain month however that is not true in certain month. This indicates that the anomalies in this market is still evident. The overall market can best describe as AMH.

The MOY Effect for BSE market is represented in Figure 4.3(c). The BSE month of the year effect has produced a significant negative return through the sample period during 1990-1992, 1996-1998,2002-2004,2008-10 in January and the excess return behave in a switching manner (Type 3). February effect appears to be significant during 1996-1998 sample period and disappear, thus market is said to be move toward efficient (Type 2). The April effect seems to be a turn of the financial effect, which is corollary to the January effect report assertion that anomalies exist overtime and behave in adaptive manner (Type 4). May, October, and November effect show no significant market reaction and excess return move in unpredicted manner over different sub-period and can be classified as perfect efficient (Type 1). The September effects show an Adaptive nature (Type 4), a positive return followed by a negative excess return. The overall market can be classified as adaptive market.

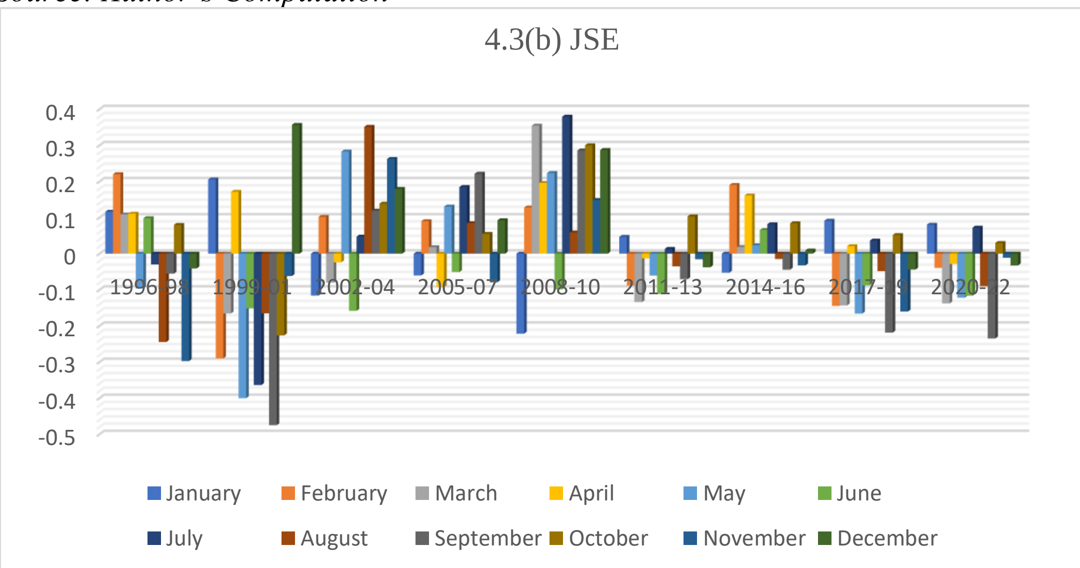
The estimate result of the MOY effect for IBOVESPA Market is depicted in Figure 4.3(e). The January effect in IBOVESPA exhibit adaptive behaviour (Type 4) a negative effect during 1990-1992 followed by a positive return, similar during 2014-2016 and 2017-2018. March, April and June effect appear to efficient until 2014 and exhibit positive excess return during 2014-2016 (Type 5), ensuring MOY anomaly is still valid. A significant positive return and a negative excess return exhibit in July, August, September and October, these months show an adaptive nature (Type 4). November and December effect show monthly anomaly during 1992-1995, 1991-2001, however the market is moving toward efficiency (Type 2). The overall market indicates these monthly anomalies occurred under different time period of the sample, which can be classified as adaptive market.

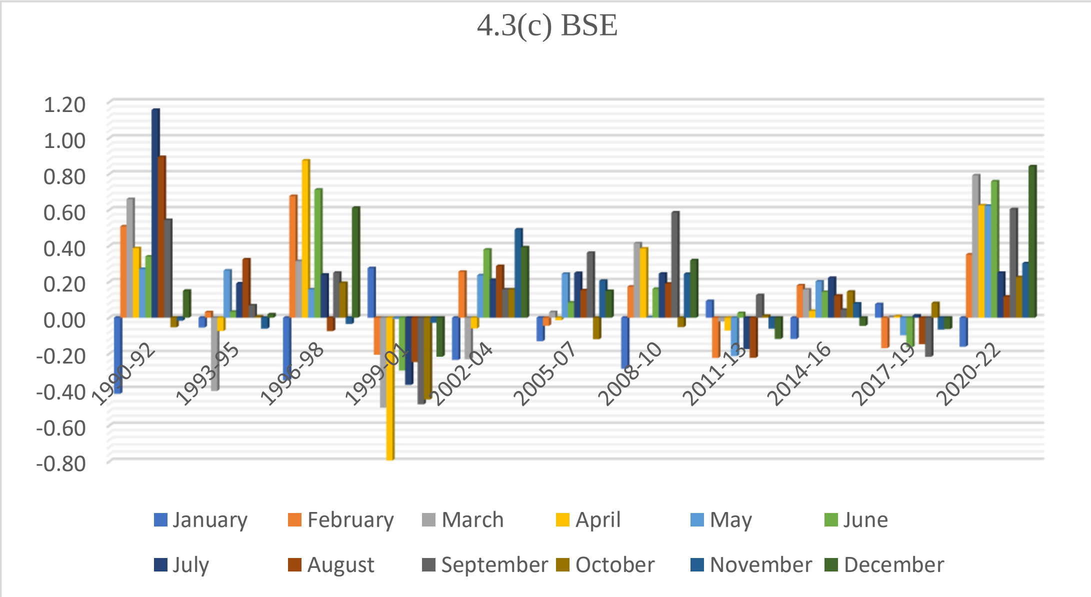
The estimate result of the MOY effect for IBOVESPA Market depicted in Figure 4.3(e) show the January effect provides a market inefficiency in 1996-1998 and the market moves toward efficiency. Further moves back to inefficient market during 2017-19, implies the market behave in a switching manner (Type 3). September, November and December effect exhibit Type 2 market classification, the inefficiency disappear after 1992. The February and March excess return behave in a switching manner (Type 3). August effect show no significant market reaction and excess return move in unpredicted manner over different sub-period and can be classified as perfect efficient (Type 1). The February, March, April, May and October effects show market inefficiency overtime and an adaptive nature (Type 4). The overall market can be classified as anomaly switch (Type 3).

Figure 4.3: Estimate coefficient of three-year fixed window month of the year effect using GARCH (1,1) estimation in BRICS markets

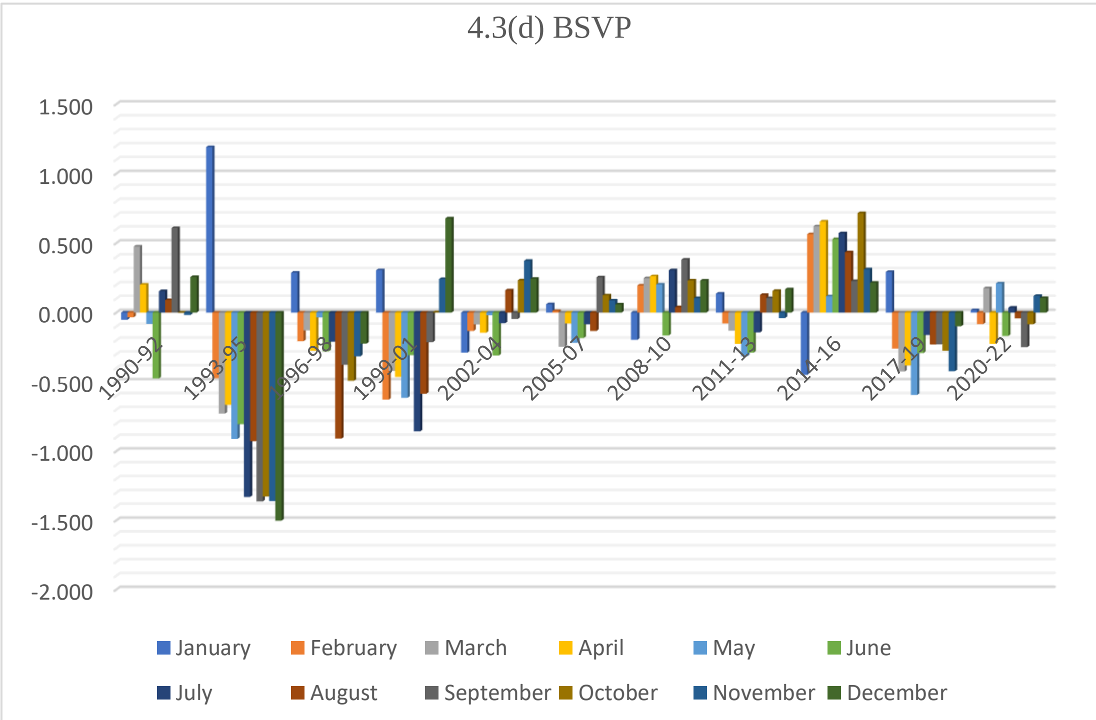


Source: Author's Computation

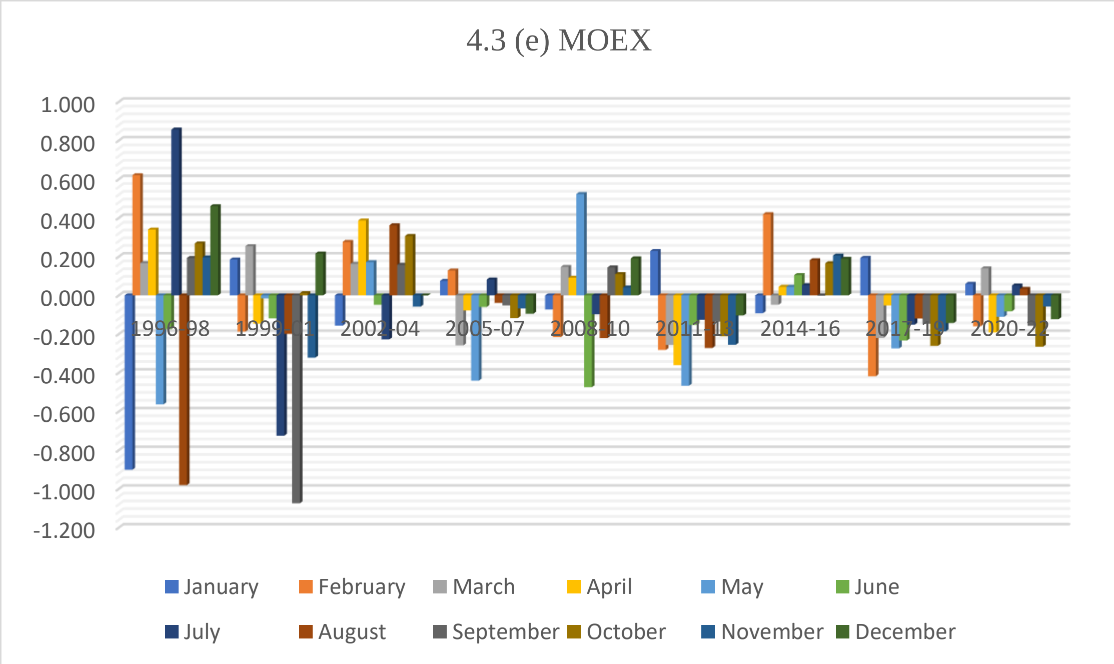




Source: Author's Computation



Source: Author's Computation



Source: Author's Computation

4.5.5 Time varying month of the year in G5 markets

The estimate coefficient of the MOY effect for CAC 40 Market is represented in Figure 4.4(a). The January and December effect on CAC 40 is found to be efficient overtime except during the period during the great financial crisis 2008-10. May effect was found to be significant during 1996-1998 and 2017-2019 (Type 2). July, August and November effect show the anomaly switch over different sub periods (Type 3). The rest of the month can be best described as the efficient market behaviour (Type 1). The overall market can be best described as type 2; the inefficient market exists in certain degree however the market is moving towards efficient market (Type 2).

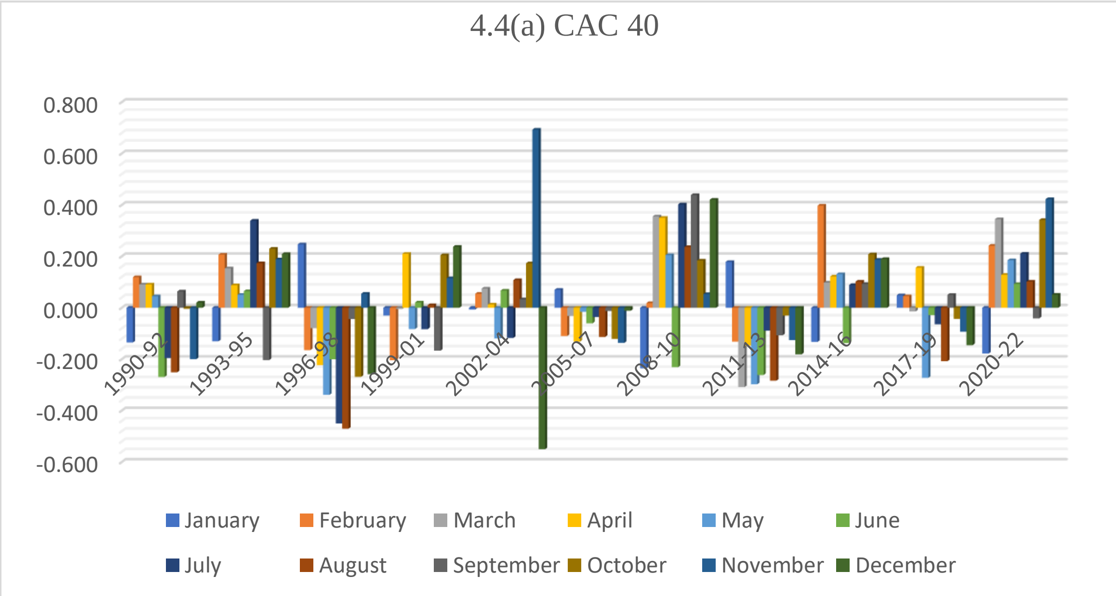
The estimate coefficient of the MOY effect for DAX 30 Market is represented in Figure 4.4(b). The January, August, and December effects exhibited market inefficiency initially, but the market moves towards efficiency during 2008-10 period, only to revert to inefficiency afterwards (Type 4). The June effect showed a consistent movement towards market efficiency. In contrast, the February, March, April, May, and November effects displayed a general trend towards market efficiency (Type 2), indicating a gradual reduction in inefficiencies over time. The July, August, and September effects exhibited anomalous behaviour, with the market switching between efficient and inefficient periods (Type 3), suggesting that these months are particularly susceptible to market dynamics and structural changes. Overall, the market can be best described as exhibiting type 2 behaviour, where inefficiencies exist to a certain degree, but the general trend is towards increased efficiency.

The estimate coefficient of the MOY effect for FTSE 100 Market is represented in Figure 4.4(c). The January effect show an adaptive nature (Type 4), with significant positive returns during 1996-1998 and 2008-2019, followed by negative returns. Conversely, the August effect demonstrated a significant reverse pattern, implying that market anomalies are still valid and persistent in the FTSE 100 index. October effect provides in efficiency during 1993-1995, then moved toward efficiency (Type 2). May, June, and November effect show no significant reactions, unpredictable excess returns, suggesting perfect efficiency (Type 1). Overall market behaviour is of switching manner (Type 3), oscillating between efficiency and inefficiency across different months and sub-periods, reflecting an adaptive and dynamic market.

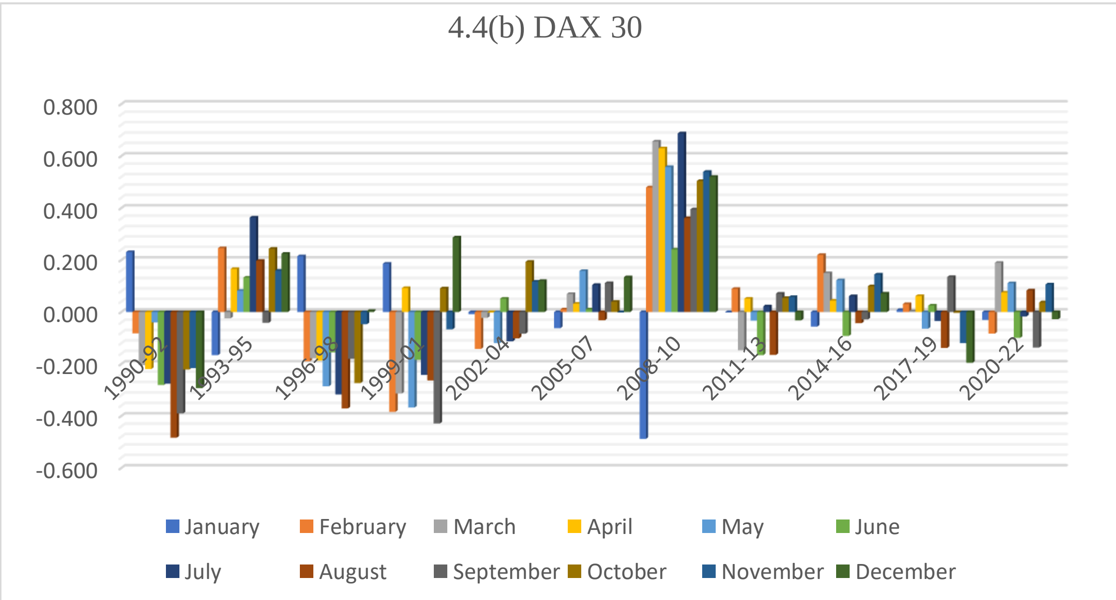
The estimate coefficient of Nikkei 225 Market MOY effect is represented in Figure 4.4(d). The analysis of seasonal effects on the Nikkei index reveals a switching pattern across different sub-periods. The January effect was found to be efficient until 2013, after which the market moves towards inefficiency, implying an anomaly switch (Type 3 behaviour). Conversely, the April effect exhibited the reverse pattern, with an initial inefficiency followed by a move towards efficiency. The May, July, and September effects demonstrated a significant negative return followed by a positive return, indicating the presence of market anomalies during these months (Type 3). Overall, the month-of-the-year effect on the Nikkei index exhibited a switching pattern in the coefficient of returns over different subperiod periods.

The analysis of the month-of-the-year effect on the S&P 500 market as shown in Figure 4.4(e) reveals a diverse range of behaviours across different months and sub-periods. The January effect exhibited a switching pattern (Type 3), with market inefficiency observed during 2002-2004, followed by a move towards efficiency, and then a reversion to inefficiency during 2017-2019 period. The August effect initially displayed inefficiency, which was subsequently followed by a transition towards market efficiency. Conversely, the September effect is found to exhibit perfect market efficiency (Type 1) throughout the examined period. Interestingly, the remaining months exhibited a reverse pattern, starting with an initial state of efficiency and subsequently transitioning towards market inefficiency over time. Overall, the S&P 500 index can be classified as exhibiting a disappearing anomaly behaviour (Type 2).

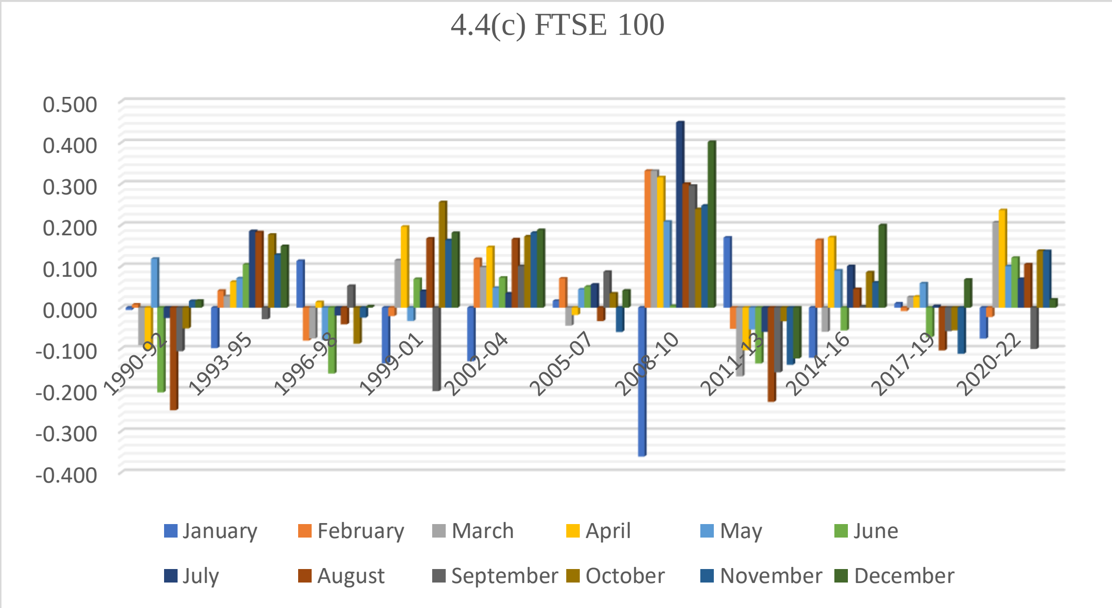
Figure 4.4: Estimate coefficient of three-year fixed window month of the year effect using GARCH (1,1) estimation in G5 markets



Source: Author's Computation

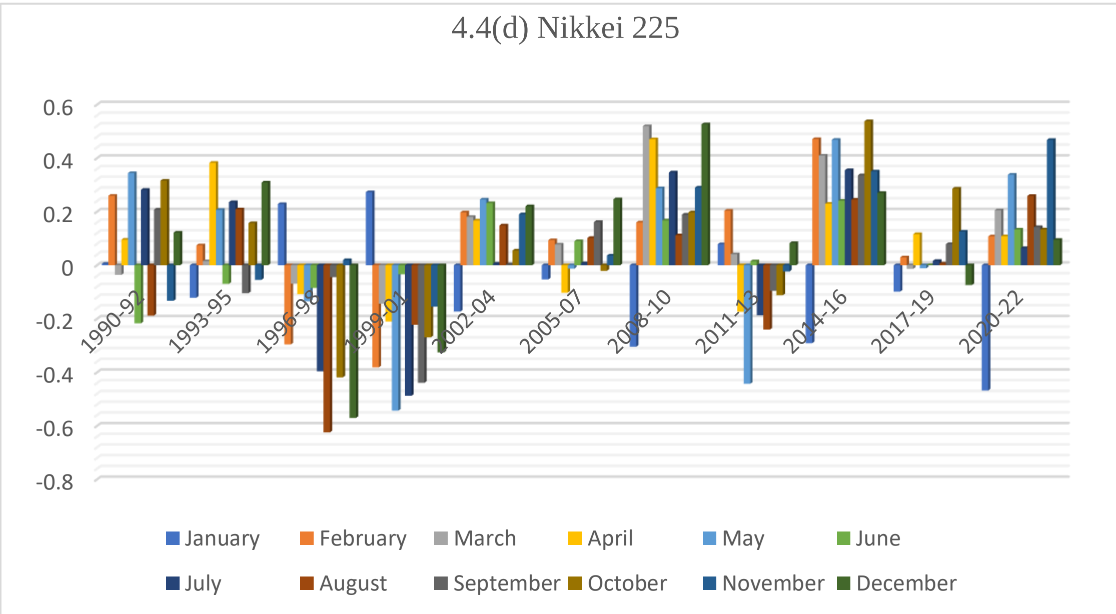


Source: Author's Computation



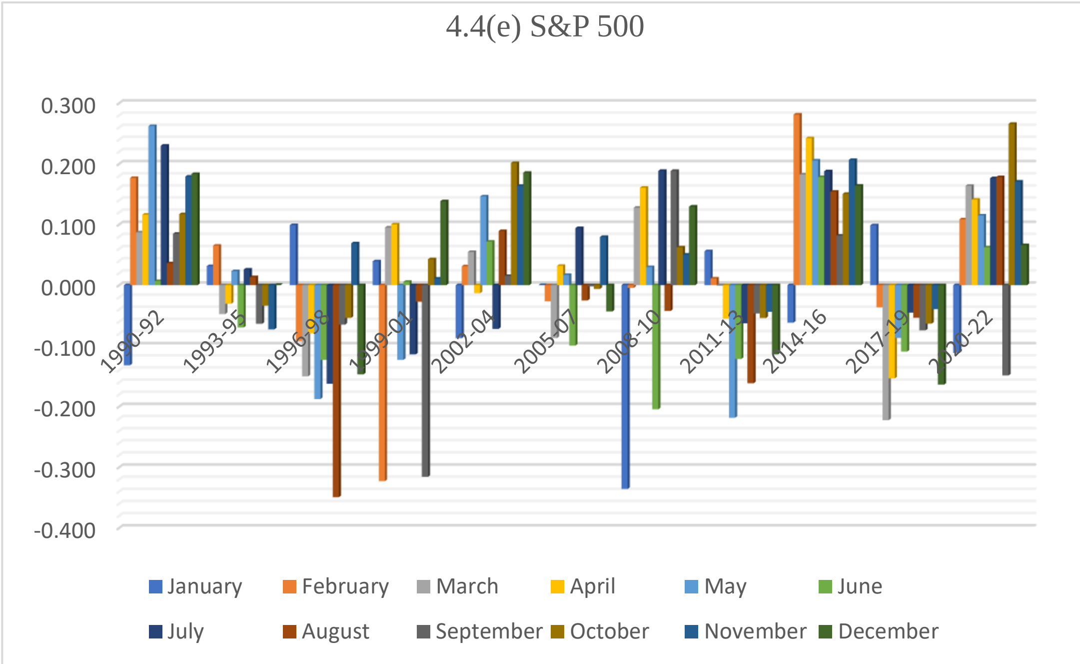
4.4(c) FTSE 100

Source: Author's Computation



4.4(d) Nikkei 225

Source: Author's Computation

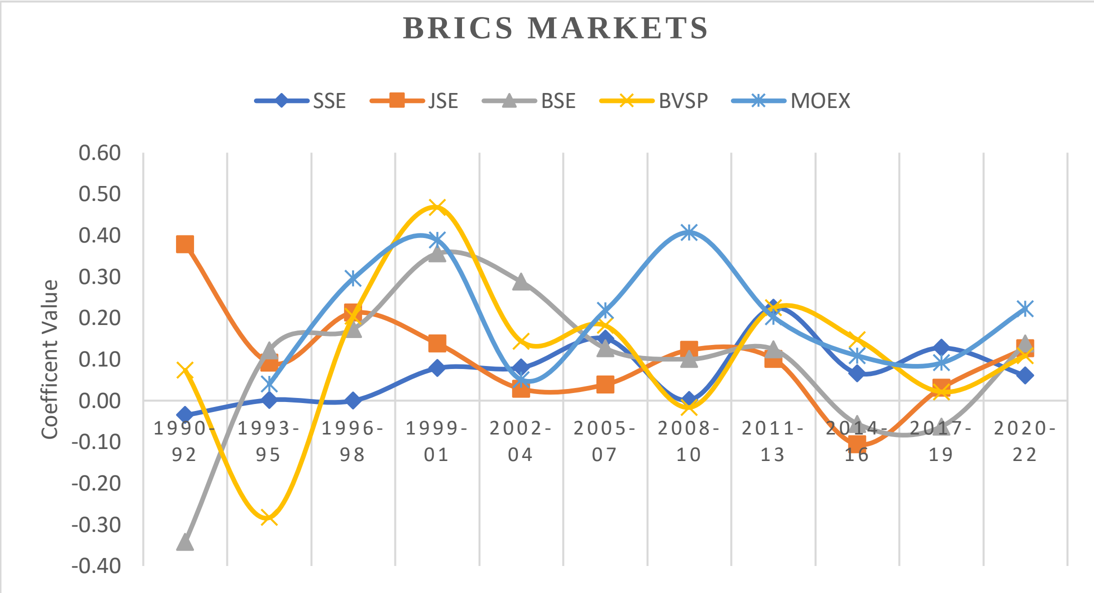


Source: Author's Computation

4.4.7 Time varying turn of the month effect in BRICS markets

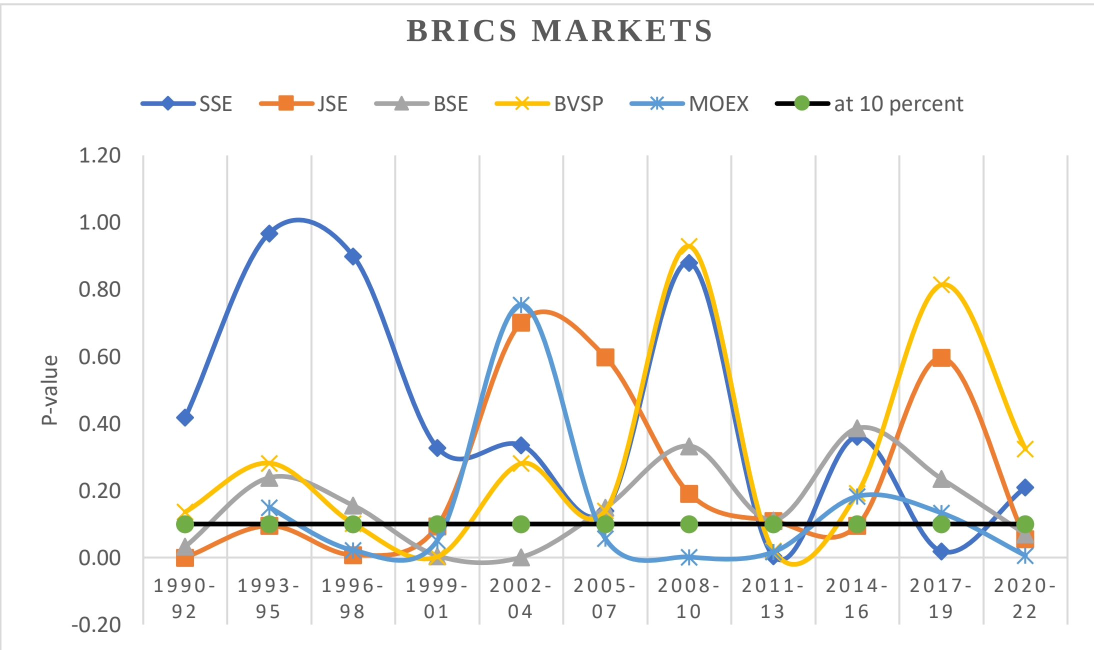
The findings on the turn-of-the-month (TOM) effect in BRICS markets are presented in Figure 4.5, and the corresponding p-values are shown in Figure 4.6. The Shanghai Stock Exchange (SSE) exhibited perfect market efficiency (Type 1) during 1993-1995 and 1996-1999, but displayed inefficiency with positive returns during 2011-13 and 2017-18. The SSE portrays a trivial TOM effect and time variation, complying with the AMH paradigm (Type 4). The Johannesburg Stock Exchange (JALSH) showed significant positive TOM returns from 1990-2001 (Type 5), then transitioned to efficiency (Type 2), and later exhibited a switch from negative to positive returns (Type 3), satisfying the AMH principle. The Bombay Stock Exchange (BSE) signified market anomalies, outperforming monthly returns during 1999-2001, 2002–2004, and 2020-2022. The Moscow Exchange (MOEX) exhibited persistent significant positive excess TOM returns, classified as market inefficiency throughout (Type 5). The São Paulo Stock Exchange (IBOVESPA) generated positive excess TOM returns in nearly all subperiods, with only two subperiods showing slightly negative excess returns, categorized as type 5.

Figure 4.5: Estimate coefficient of three-year fixed window turn of the month effect using GARCH (1,1) estimation in BRICS markets



Source: Author's Computation

Figure 4.5: Estimate p-value of three-year fixed window turn of the month effect using GARCH (1,1) estimation in BRICS markets



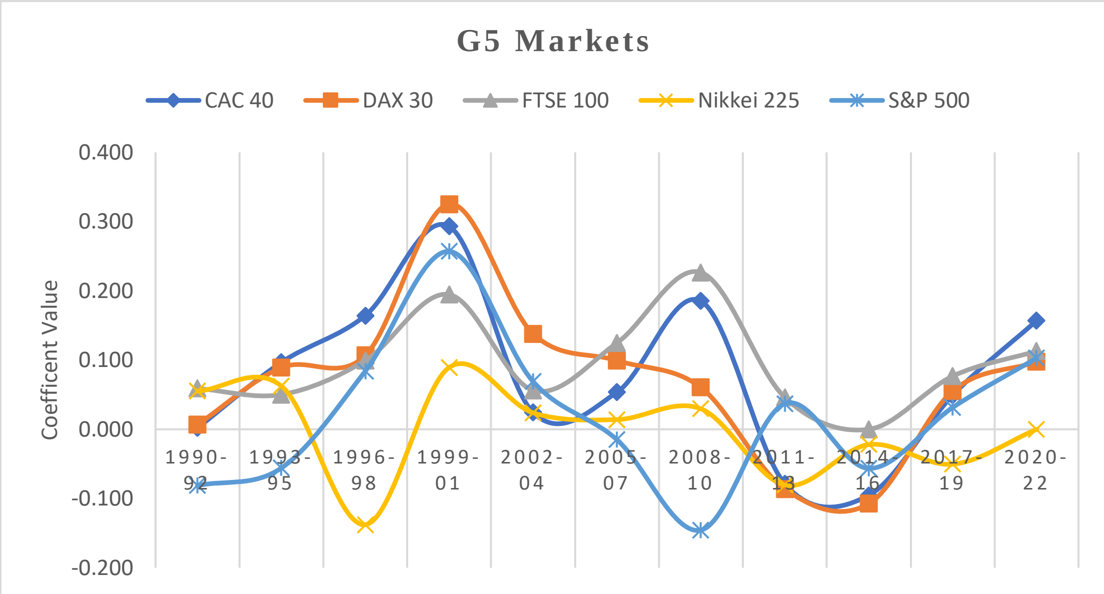
Source: Author's Computation

4.4.8 Time varying turn of the month effect in G5 markets

The results for the TOM effect in developed markets are documented in Figure 4.7, with p-values depicted in Figure 4.8. The CAC 40 exhibited significant positive excess TOM returns during 1996-1998 and 1999-2001, but moved towards efficiency with negative returns in later periods (Type 2). The DAX 40 showed a trivial episodic TOM effect before the global financial crisis and subsequently transitioned to efficiency (Type 2). The FTSE 100 displayed significant episodic TOM effects with positive returns during 1996-2001 and 2005-2010. However, since 2011, no subperiod exhibited positive excess returns, indicating an adaptive nature (Type 4). The Nikkei 225 did not show a significant TOM effect, with excess returns fluctuating between positive and negative throughout the sample period. The S&P 500 appeared to move towards efficiency with negative returns across most subperiods. However, the TOM effect during 1999-2001 and 2014-16 portrayed market inefficiency with positive returns, suggesting an adaptive behaviour (Type 4) over time.

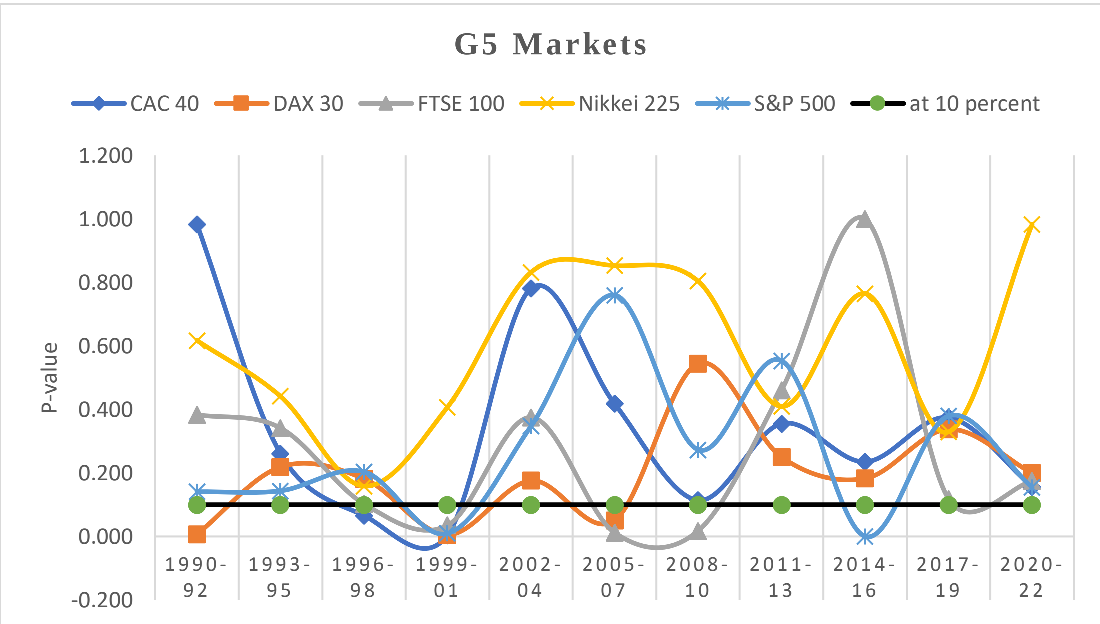
Comparing these findings with the earlier results on BRICS markets, there are some consistencies and divergences. Similar to some BRICS markets like the SSEC and JALSH, certain developed markets (CAC 40, DAX 40, FTSE 100) exhibited a transition from inefficiency (positive TOM returns) to efficiency (negative TOM returns), classified as type 2. Additionally, the adaptive nature of the TOM effect, categorized as type 4, was observed in both the FTSE 100 (after 2011) and the S&P 500, consistent with the SSE's behaviour. However, the persistent market inefficiency (Type 5) observed in some BRICS markets like the JALSH, SENSEX, MOEX, and IBOVESPA was not evident in the developed markets analysed. Furthermore, the Nikkei 225 did not exhibit a significant TOM effect, unlike the BRICS markets, which generally displayed some form of episodic anomaly.

Figure 4.6. Estimate coefficient of three-year fixed window turn of the month effect using GARCH (1,1) estimation in G5 markets



Source: Author's Computation

Figure 4.7. Estimate p-value of three-year fixed window turn of the month effect using GARCH (1,1) estimation in G5 markets



Source: Author's Computation

4.6 Possible excess return from trading strategy

When confronted with any stock market anomaly, an important inquiry arises: can investors leverage these calendar anomalies to garner returns that surpass the market's performance? In this section, we examined whether an implied trading strategy (ITS) based on identified calendar anomalies generates higher returns than a simple buy-and-hold (BH) strategy. The profitability of implied trading strategies (ITS) based on calendar anomalies differs significantly between developed and developing markets. Testing these hypotheses will provide insights into the practical applicability and economic significance of calendar anomalies in stock markets.

The buy-and-hold (BH) strategy adheres to the principle of acquiring a stock or portfolio at the beginning of the study period (in this case, 1 January 1990) and retaining ownership until the conclusion of the examination period (31 December 2022). This passive investment approach eschews active trading and aims to capture the long-term capital appreciation of asset(s) over the entire duration of the study.

The Implied Trading Strategies (ITS) are employed to potentially exploit various calendar anomalies derived from the methodologies in previous studies (Khuntia & Pattanayak, 2020; Urquhart & McGroarty, 2014) and are structured as follows:

Monday Effect: The ITS for the Monday effect involves establishing a long position on Tuesday and subsequently liquidating that position on the immediately following Monday. This cycle was then iteratively replicated until 31 December 2022. The underlying premise is the historical observation that stock returns tend to be lower on Mondays than on other weekdays, a phenomenon known as the Monday or weekend effect. By going long on Tuesdays and closing out positions on Mondays, investors aim to capitalise on the potential for higher returns during the intervening period.

January Effect: In this case, a long position is initiated at the closing price on the last trading day of December, and a corresponding short position is established at the closing price on the final trading day of the immediate subsequent January. This process is repeated until 31 December 2022. The January effect refers to the observed tendency for stock prices to exhibit above-average returns in the month of January, potentially due to factors such as window dressing by investment managers and the reinvestment of year-end bonuses by individuals. By adopting a long position in late December and closing it at the end of January, investors attempt to capture the potential price appreciation associated with this anomaly.

Turn-of-the-Month (TOM) Effect: For the TOM effect, the ITS is designed to purchase the underlying assets at the closing price of the final trading day of a month and subsequently sell those assets at the closing price of the fifth trading day of the next month. This process was repeated until the last day of the study period. The TOM effect is characterised by the observation that stock returns tend to be higher around the turn of the month, potentially because of factors such as the reinvestment of regular income streams or the clustering of cash flows. By establishing a long position at the end of one month and closing it a few days in the next month, investors aim to benefit from the anticipated price appreciation associated with this calendar anomaly.

Sell in May (SIM) effect: In this case, establishing a long position in the underlying asset (buy stock) at the closing price of the last trading day in April. Maintaining this long position throughout the winter months (November to April). Liquidating the long position at the closing price on the last trading day of April the following year. This cycle is repeated annually until the end of the study period (31 December 2022). The rationale behind this strategy is to be invested in the market during the historically favourable winter months and to shift to a short position during the potentially underperforming summer months. It also refers to the observed tendency for stocks to experience lower returns during the summer months (May to October) than during the winter months (November to April).

The results for the potential profitability of exploiting calendar anomalies through the implementation of simple trading strategies for the BRICS countries are presented in Table 4.9. In Panel A, for the SSE, the Monday effect and January effect trading strategies failed to outperform the buy-and-hold strategy, indicating that these anomalies could not be traded effectively using the implied trading strategy (ITS) in this market. However, the TOM effect and SIM effect strategies outperformed the buy-and-hold approach by 0.49% and 0.37%, respectively, suggesting potential exploitable opportunities. In the case of the IBOVESPA in panel B, the ITS for the January effect, TOM effect, and SIM effect underperformed the buy-and-hold strategy, with annual returns of 7.32%, 1.27%, and 6.09%, respectively. Notably, the Monday effect trading strategy marginally outperformed the buy-and-hold approach by 0.04% annually, indicating the potential for more substantial gains if implemented effectively on a larger scale or over an extended period. Panel C show JALSH exhibited outperformance of the Monday effect and SIM effect trading strategies over the buy-and-hold strategy, with excess returns of 0.29% and 0.21%, respectively. However, the January effect and TOM effect strategies underperformed, with annual returns of -6.48% and -1.13%, respectively. Panel D represent MOEX, the ITS for the Monday effect, January effect, and SIM effect generated lower returns than the buy-and-hold strategy, with annual returns of 1.80%, 4.21%, and 5.18%, respectively. Conversely, the TOM effect strategy outperformed the buy-and-hold approach by 1.01% per annum. Finally, in case of BSE in Panel E, no evidence of any positive return by ITS was found.

In summary, the buy and hold strategy performs better than ITS calendar effects in most cases. The only exception is the large outperformance of ITS over BH for the Monday effect in the South Africa market. Otherwise, BH generally produces higher returns than calendar based ITS strategies in BRICS markets. We failed to reject the null hypothesis H_{04a}, as the evidence indicates that buy-and-hold strategies generally outperform trading strategies based on calendar anomalies.

Table. 4.9: The result for calendar anomalies using the Buy and hold trading strategy and implied trading strategy in BRICS markets

Anomalies	Trade	Trade Exposure	ITS Profit	BH profit	Difference	Annualised % Difference
Panel A: SSEC						
Monday	6332	80%	257.33	318.59	61.25	-0.67%
January	629	8%	16.54	318.59	-302.05	-8.83%
TOM	2309	29%	372.43	318.59	53.84	0.49%
SIM	5138	65%	358.19	318.59	39.6	0.37%
Panel B: IBOVESPA						
Monday	6218	81%	2,057.87	2,083.01	25.14	0.04%
January	636	8%	183.17	2,083.01	-1899.74	-7.32%
TOM	2269	29%	1,410.31	2,083.01	-672.7	-1.21%
SIM	5024	65%	278.56	2,083.01	-1804.45	-6.09%
Panel C: JALSH						
Monday	5652	80%	2,797.01	270.53	2526.48	0.29%
January	584	8%	42.81	270.53	-227.72	-6.48%
TOM	1980	25%	198.13	270.53	-72.4	-1.13%

SIM	4636	66%	289.21	270.53	18.68	0.21%
Panel D: MOEX						
Monday	5110	81%	171.94	307	-135.06	-1.80%
January	555	9%	77.62	307	-229.38	-4.21%
TOM	1824	29%	423.42	307	116.42	1.01%
SIM	4159	66%	-53.61	307	-360.61	-5.18%
Panel E: SENSEX						
Monday	6390	81%	117.98	435.24	-317.26	-3.92%
January	656	8%	-8.79	435.24	-444.03	-17.23%
TOM	2351	23	303.69	435.24	-131.55	-1.07%
SIM	5138	65	209.24	435.24	-226	-1.31%
Source: *Author's computation*						

The results in Table 10 show the potential profitability of exploiting calendar anomalies through simple trading strategies for the G5 countries. In Panel A for the French CAC 40 index, the January and Turn-of-the-Month (TOM) effect trading strategies did not outperform the buy-and-hold strategy. This means these anomalies could not be effectively traded on the CAC 40 market. However, the Monday effect and Semi-Monthly (SIM) effect strategies did outperform buy-and-hold, with annual excess returns of 0.70% and 2.50% respectively. For the German DAX 30 in Panel B, the Monday, January, and TOM effect strategies underperformed buy-and-hold with annual returns less than the market return. Only the SIM effect strategy marginally beat buy-and-hold by 1.68% annually. This suggests the SIM anomaly could potentially offer higher gains if traded on a larger scale or longer horizon, assuming it persists.

Panel C shows for the UK's FTSE100, the TOM and SIM strategies outperformed buy-and-hold by 0.57% and 1.42% respectively. However, the January and Monday strategies underperformed with negative annual return by 0.16% and 1.63% respectively. For Japan's Nikkei 225 in Panel D, the Monday, January, and SIM strategies beat buy-and-hold with excess annual returns of 4.77%, 0.32%, and 5.14% respectively. Only the TOM strategy underperformed at -0.68%. Finally, Panel E reveals for the US S&P 500, just the SIM strategy outperformed buy-and-hold at 1.42% annually. The Monday, January, and TOM strategies all underperformed with negative annual returns versus the market return.

Given these mixed results with a majority of strategies underperforming buy-and-hold, the null hypothesis H_{04a} failed to reject. The evidence does not consistently support the claim that implied trading strategies based on calendar anomalies generate higher returns than a simple buy-and-hold strategy across G5 markets.

Table 4.10: The result for calendar anomalies using the Buy and hold trading strategy and implied trading strategy in G5 markets.

Anomalies	Trade	Trade Exposure	ITS Profit	BH profit	Difference	Annualised % Difference
Panel A: CAC30						
Monday	6819	86%	147.94	117.41	30.53	0.70%
January	701	9%	43.02	117.41	-74.39	-3.00%
TOM	2376	28%	94.3	117.41	-23.11	-0.68%
SIM	5635	71%	264.86	117.41	147.45	2.50%
Panel B: Dax40						
Monday	6707	81%	88.9	205.2	-116.3	-2.50%
January	643	8%	16.5	205.2	-188.7	-7.35%
TOM	2376	29%	142.97	205.2	-62.23	-1.09%
SIM	5500	70%	356.12	205.2	150.92	1.68%
Panel C: FTSE 100						
Monday	6712	85%	99.66	112.36	-12.7	-0.16%
January	688	9%	61.22	112.36	-51.14	-1.63%
TOM	2376	28%	135.32	112.36	22.96	0.57%
SIM	5593	64%	179.19	112.36	66.83	1.42%
Panel D: Nikkei 225						
Monday	6679	85%	92.84	19.94	72.9	4.77%
January	697	9%	22.12	19.94	2.18	0.32%
TOM	2376	28%	15.35	19.94	-4.59	-0.68%
SIM	5406	64%	93.65	19.94	73.71	5.14%
Panel E: S&P 500						
Monday	6767	86%	208.94	236.79	-27.85	-0.39%
January	1574	14%	207.51	236.79	-29.28	-0.40%
TOM	2376	28	98.86	236.79	-137.93	-2.61%
SIM	5519	70	259.62	236.79	22.83	0.28%
***Source**: Author computation*						

4. 7. Conclusion

The study investigates the presence of calendar anomalies, including the day-of-the-week effect, month-of-the-year effect, and turn-of-the-month effect, in the stock markets of BRICS countries (Brazil, Russia, India, China, and South Africa) and a group of seven developed countries (G5). The study provides evidence for the existence of calendar anomalies in both emerging and developed stock markets, although the patterns and magnitudes differ across markets and time periods. Emerging markets exhibit more pronounced calendar anomalies, particularly in the day-of-the-week and turn-of-the-month effects, while developed markets show stronger evidence of the month-of-the-year effect.

The key conclusions are as follows:

1). Day-of-the-week (DOW) Effect: The return of day of the week effects are found to be significant, except for SENSEX 30. The increase in volatility in the SSE market was found to be highest on Monday and lowest on Tuesday. The developed G5 markets exhibited significant day-of-the-week effects on the CAC 30 and FTSE 100 markets. The Thursday effect shows heightened volatility in the CAC30, NIKKEI 225, and S&P 500 returns. A significant positive Friday effect is notable in the NIKKEI 225 index. The empirical findings rejected the null hypothesis H_{02a} in both BRICS and G5 markets and the DOW effects is more relevant in developing markets than in developed markets.

2). Month of the Year (MOY) Effect: There is a significant month-of-the-year effect on the BRICS and G5 market, leading to the rejection of null hypothesis H_{03a}. Both emerging and developed markets show widespread MOY effects show a significant monthly seasonality. Interestingly, these MOY effects are more pronounced in developed markets than in emerging markets. when examining volatility patterns, emerging markets exhibit greater volatility persistence compared to their developed counterparts.

3). **Turn of the Month (TOM) Effect**: The TOM effect was found significant in IBOVESPA, MOEX, SSEC, and SENSEX 30. SENSEX 30 shows the highest volatility and IBOVESPA shows the lowest. The null hypothesis H_{03a} was failed to reject in the JALSH market. The TOM effect in the G5 market was found to be significant in all markets, except the NIKKEI 225 Market. Developed markets do not exhibit volatility associated with TOM, except for FTSE 100.

4). **Adaptive Calendar Effect**: Emerging markets like JALSH, MOEX, and SSE showed significant adaptive market anomalies with excess returns, while BSE and IBOVESPA moved towards efficiency. Developed markets exhibit adaptive market behaviour, oscillating between efficiency and inefficiency across different sub-periods. Based on these observations, we fail to reject null hypothesis H_3, which posits that there is a significant adaptive nature to calendar effects in these markets.

5. **Potential Profitability from Trading Strategies:** Some trading strategies based on calendar anomalies outperformed the buy-and-hold strategy in certain markets, suggesting potential exploitable opportunities. However, the performance of trading strategies varies across markets and anomalies with no consistent pattern. Based on this mixed evidence, we failed to reject the null hypothesis H_{04b}, which suggests that there is no systematic advantage to calendar-based trading strategies over simple buy-and-hold differ in emerging and developed market, except for SIM developed market.

This study highlights the presence of calendar anomalies in both emerging and developed markets, with significant time-varying and adaptive behaviour, supporting the Adaptive Market Hypothesis (AMH). The time-varying analysis reveals that calendar anomalies are not static and can exhibit adaptive behaviour, with markets transitioning between periods of efficiency and inefficiency. This finding supports the Adaptive Market Hypothesis, which suggests that market efficiency is a dynamic process that is influenced by changing market conditions, investor behaviour, and the incorporation of new information. Overall, this study contributes to the ongoing debate on market efficiency and the presence of calendar anomalies, emphasising the dynamic nature of financial markets and the need for continuous monitoring and adaptation to exploit potential inefficiencies or mitigate associated risks.

CHAPTER 5: Investors sentiment toward the market during natural calamities

5.1. Introduction

Researchers have proposed various theories and examined numerous potential determinants to explain stock market fluctuations. Cutler et al. (1989) found that a significant portion of market movements could not be attributed to news about fundamentals such as macroeconomic factors or corporate earnings. This leads to the proposition that investor psychology and sentiment play a crucial role in driving market dynamics. Numerous studies have also examined the role of macroeconomic variables, such as interest rates, inflation, economic growth, and monetary policy, in influencing stock market behaviors (Humpe & Macmillan, 2009; Luís et al., 2021). More recently, researchers have investigated the impact of non-economic events and phenomena on market movement. For instance, studies have analysed the effects of political events (Bialkowski et al., 2008), natural disasters (Worthington & Valadkhani, 2004), and sports outcomes (Edmans et al., 2007) on stock market performance. Existing literatures suggest that natural events have a significant impact on stock movement, including cloud clever (Saunders, 1993), daylight (Kamstra et al., 2000:2002), sunshine (Hirshleifer & Shumway 2003), and temperature (Cao & Wei 2005). The same is true in the market: the role of sentiment toward the Covid-19 pandemic in the global market.

In recent decades, approximately 300 natural disasters have struck, affecting approximately 150 million people and resulting in an economic cost of $100 billion annually . According to the PLC report, these events have far-reached high levels in 2023 with 398 natural disasters, surpassing the average 21st century natural disaster. The profound impact of natural disasters on human life, infrastructure, and economic systems has garnered significant attention from academic researchers and practitioners in recent years. This complex interplay between natural disasters and financial systems has emerged as a critical area of study, with scholars seeking to understand and quantify the multifaceted ramifications of these events on economic stability and market dynamics.

The primary objective of this chapter is to investigate the effects of natural disasters on the Indian equity market. Specifically, we analyse how catastrophic events influence stock market performance and returns in the Indian equity market. Furthermore, this chapter explores the co-movement and potential linkages between natural disaster sentiments or perceptions of natural disasters and stock market returns. It would be interesting to comprehend whether shifts in collective sentiment towards these catastrophic occurrences exhibit any noticeable patterns or relationships with equity market fluctuations.

This chapter is organised into distinct sections. The first section provides a comprehensive overview of natural disasters, detailing the various types of catastrophic events that occurred during the study period under examination. The second section reviews the existing literature pertinent to the research topic, and the third section provides the methodology employed throughout this chapter, including the intricate process of constructing and quantifying the investor sentiment index. The fourth section examine the impact of natural disasters on sectoral index returns and assesses the relationship between disaster sentiment and sectoral stock returns. Finally, section five provides a summary and conclusion.

5.1.1 Overview of Natural Disaster

A disaster can be characterised as a profound and disruptive event that severely impairs the normal functioning of a community or society, leading to widespread and multifaceted consequences across various domains, including loss of life, damage to material resources, economic instability, and environmental degradation (Coppola, 2015; Lindell, 2013). The magnitude of such an occurrence overwhelms the affected region's capacity to cope effectively by using its own available resources and means (UNDRR, 2009). These catastrophic events exceed the inherent resilience and response capabilities of the impacted area, necessitating external assistance and support to mitigate the far-reaching losses and impacts caused by the disaster (Cutter, 2016).

A natural disaster, in particular, is a naturally occurring phenomenon that abruptly and severely disrupts a society's normal operations, resulting in significant property damage and loss of human life to the extent that the society's usual social and economic institutions are rendered unable to restore order independently (Bryant, 2005; Hyndman & Hyndman, 2016). From this perspective, various natural events, whether stemming from microenvironmental occurrences or broader phenomena, can be considered disasters for society if they overwhelm their coping mechanisms and resilience (Wisner et al., 2004).

Natural disasters encompass a wide range of events, including but not limited to earthquakes, hurricanes, tsunamis, volcanic eruptions, floods, droughts, wildfires, and landslides (Guha-Sapir et al., 2004). Each type of disaster poses unique challenges and impacts that require tailored preparedness, response, and recovery strategies (Cutter, 2016; Lindell, 2013).

Kahn (2005) documented those countries with coastline and near fault lines are more likely to suffer consequence of windstorm, hurricanes, tsunami and earthquake. He found that Asian countries are 28.5 percent point more likely to experience a disaster in a given year as compared to Africa. India is one of the nations with the greatest risk of catastrophe in the world. As per world risk report (2022), India with world risk index 42.31 percent is the second highest disaster risk next to Philippines (46.82). As per UNICEF report India,[4] with 27 of its 29 states and seven union territories subject to natural disasters such as cyclones, earthquakes, landslides, floods, and droughts. In the last few decades frequent of extreme weather and intensity disasters hit India; Andhra Pradesh cyclone of 1977, Bangladesh cyclone in 1985; Latur earth quake 1995; Gujarat earth quake, 2001 Indian ocean tsunami of 2004; North Indian flood in 2014; Indian heat waves 2016; Kerala floods in 2019 cause untold damage and several thousand deceases has increased in many parts of the countries.

5.1.2 Pattern of natural disaster under the study period

India is a region that offers pertinent instances in terms of natural disasters and their economic effects for a number of reasons. The first is that the area is

[4] https://www.unicef.org/india/what-we-do/disaster-risk-reduction

geographically vulnerable to different kinds of natural dangers. However, the economies in this region experience natural calamities with varying frequency and origins. As a result, different types of disasters are occurred in different regions. The study of the economic consequences of natural disasters has traditionally focused on specific regions where such events are prevalent and data is more readily available. However, with recent advancements in technology, various disasters are now being documented more accurately and comprehensively, providing researchers with a broader range of data sources to analyze the impacts on economies. This list covers a wide range of catastrophic events in India under study is represented in Table 5.1. The lists are obtained from EM-DAT (Emergency Events Database). The database compiles data from multiple sources, including UN agencies, national disaster management institutes, insurance companies, research institutions, and non-governmental organizations. To overcome limitations and ensure comprehensive information, the research incorporates reports from the National Disaster Management Authority of India. These reports provide a more robust and inclusive assessment of the natural disasters under study. By triangulating data from the EM-DAT database with the National Disaster Management Authority reports, the research aims to present a more accurate and complete picture of the natural disasters in India, their consequences, and the extent of their impact on affected regions and populations. Between January 1, 2013, and December 31, 2022, India experienced 112 natural disasters, out of which 60 met the disaster criteria: cause 20 or more fatalities, affect at least 1,000 individuals, or declaration of a state of emergency and a call for international assistance. According to the information provided, floods are the most prevalent type of natural disaster in India, accounting for more than 50 percent of the overall disasters in the country. The second most common disaster is tropical cyclones. The breakdown of different types of natural disasters in India is shown in Table 5.1.

Table 5.1: Chronological list of natural disaster occurrences under study

Date	Disaster Sub-group	Disaster type	Note(s)
15th May – 15th June, 2013	Meteorological	Heat wave	The heatwave primarily affected Central, East, North and Northwest parts of India including states like Andhra Pradesh, Odisha, Jharkhand, Uttar Pradesh, Delhi, Rajasthan. Maximum temperatures consistently over 45°C, and even going above 47°C in some places. leading to over 557 deaths along with power cuts/health issues.
12th -27th June 2013	Hydrological	Flood	The Uttarakhand flash floods and landslides of June 16, 2013 resulted in one of the worst disasters the state All 13 districts were affected but the worst hit districts were Bageshwar, Chamoli, Pithoragarh, Rudraprayag and Uttarkashi. Heavy rainfall caused rapid torrents of flood water and debris flow through mountain areas, destroying roads and buildings and burying many villages. with particularly high death tolls estimated between 169 to over 6,000. State of emergency declared.
9th – 10th July, 2013	Hydrological	Flood	The monsoon rains started on June 16 and continued until July 15, affecting various regions. In the early phase of the Southwest Monsoon. It compounded the damage caused by the Uttarakhand tragedy in June 2013. Reported death - 174; No of affected areas: 50000 peoples
22nd – 27th August, 2013	Hydrological	Flood	August rainfall led to devastating floods in Odisha, Bihar, Uttarakhand Assam, Arunachal Pradesh states resulting in extensive infrastructural and agricultural damage. Over 73 deaths showed the human toll. Several national highways and rail routes got blocked, disrupting transportation.
12th October, 2013	Meteorological	Cyclone Phailin	The storm made landfall near Gopalpur in Odisha. Other states affected were Andhra Pradesh, Jharkhand and West Bengal. An extremely severe cyclonic storm with wind speeds of up to 210 km/hr. Nearly 11 million people were impacted along the path of the cyclone. Advance preparation and mass evacuation efforts led to minimized loss of human lives. Total 47 deaths were reported.
16th- 30th December, 2013	Meteorological	Cold wave	Temperatures dropped below 3°C in some places such as Churu, Amritsar and Adampur which is 4-7 degrees below normal. Region affected North India and Central India, including states like Uttar Pradesh, Punjab, Haryana, Madhya Pradesh and Rajasthan. Over 249 death reported. Rabi crop damage reported. Increase in fog related incidents disrupting road, rail and air transport
20th – 24th January, 2014	Meteorological	Cold wave	Minimum temperatures dropped below freezing point in some places like Amritsar (-0.8°C) and Pahalgam (-16°C). Region affected including Jammu & Kashmir, Delhi, Punjab, Haryana, Uttar Pradesh and North Rajasthan. Over 140 reported dead mainly due to hypothermia and heart attacks triggered by extreme cold conditions.
18th -22th April, 2013	Meteorological	Convective storm	a severe dust storm hit Bikaner district in Rajasthan along with adjoining areas. Wind speeds reached over 100 kmph accompanied by rainfall/hailstorm. At least 27 deaths were reported, mainly due to wall collapses and falling trees/electric poles that injured people.

26th -28th June, 2013	Hydrological	Riverine flood	Major riverine floods impacted states of Assam, Meghalaya, Bihar and Uttarakhand due to heavy monsoon rains. Over 2 million people affected. Kaziranga National Park submerged. Hundreds of villages inundated and 27 deaths reported
17th -28th August, 2014	Hydrological	Riverine Flood	Monsoon floods continued to ravage parts of India, especially states like Odisha, West Bengal, Bihar, Assam and Uttar Pradesh. By August-end, at least 258 people had died across India since June due to floods triggered by heavy monsoon rains. Over 2 million were displaced. Thousands of villages, crops and large areas were inundated, and damages ran into millions of dollars.
1st -6th September, 2014	Hydrological	Flood	Worst hit states were Jammu & Kashmir, Punjab, Haryana, Uttar Pradesh, Assam and Meghalaya. Heavy rainfall triggered flash floods and landslides. At least 298 deaths reported, property damage widespread. Over 275000 peoples inundated as several rivers overflowed banks.
30th July, 2014	Geological	Landslide	A massive landslide in the village of Malin in Pune district of Maharashtra state caused the death of at least 151 people after heavy monsoon rains. Rescue and recovery efforts lasted for weeks.
12th October, 2014	Meteorological	Cyclone HudHud	Hudhud brought destructive winds of over 120 mph along with very heavy rainfall. causing extensive damage in 4 costal districts, especially in Andhra Pradesh and Odisha states. Total economic losses were estimated at over $3.4 billion. At least 124 people were killed by the cyclone, about 1,12,850 houses are partially or full destructed. Over 2,000 rescuers were deployed in the aftermath along with military relief efforts.
17th -18th December 2014	Meteorological	Cold Wave	A severe cold wave gripped parts of North and Central India in December 2014.Temperatures dropped to as low as 3-4 degrees Celsius in Punjab, Haryana, Delhi and other parts of North India. In Delhi, temperatures hit a record low of 2.9 degrees Celsius in January 2015. Dense fog conditions also set in. Several deaths as much as 24 personals related to the extreme cold temperatures were reported, especially amongst the homeless and vulnerable groups.
16th -18th March, 2014	Meteorological	Storm	Severe hailstorms hit fruit crops in Himachal Pradesh right before harvest season. This led to major crop and property damage. Parts of Uttar Pradesh were also affected by hailstorms, compounding the impact of heavy rains earlier in the month. A fatal of 27 death were recorded due to convective storm in this period.
20th -30th March, 2015	Hydrological	Flood	Heavy pre-monsoon rains in March led to flash floods in states like Jammu and Kashmir, Rajasthan, Gujarat and Eastern India. In Jammu & Kashmir, the Jhelum river and other water bodies flooded, inundating over 100 villages and affecting thousands. Saw crop damage, 2112 home are affected and 44 human life were loss.
21st April, 2015	Meteorological	Storm	A massive dust storm hit parts of North India, including states like Rajasthan and Uttar Pradesh. Wind speeds reached 90-100 km/hr, bringing traffic to a halt, uprooting trees and worsening air quality significantly. death toll 100 and affecting 125000.

20th -31st May, 2015	Meteorological	Heat Wave	An intense heat wave affected large parts of India with temperatures reaching over 45°C and even 48°C in some areas. with maximum temperatures often between 6-8 degrees Celsius above normal. Over 2,500 people died due to heat stroke and other heat-related causes as hospitals were overwhelmed with patients.
15th – 20th July, 2015	Hydrological	Flash Flood	States across North, West, East and Northeast India experienced flooding including Rajasthan, Gujarat, West Bengal, Odisha, Assam and Arunachal Pradesh. over 293 deaths reported and 5 million people were impacted by floods that displaced thousands from their homes. Relief camps were setup, rescue operations were launched and the military assisted with flood relief work.
11th -25th November	Hydrological	Flood	The northeast monsoon season brought heavy rainfalls over southern India, especially the state of Tamil Nadu in early November due to a depression in the Bay of Bengal. This resulted in devastating floods across Chennai, Kancheepuram, Tiruvallur and Cuddalore districts of Tamil Nadu. The Adyar river and others overflowed. Over 500 people died from drowning and collapsing structures during the Chennai floods. Economic losses totalled almost $3 billion. Relief camps housed over 1.8 million people displaced at the peak.
Mid-April - Mid-May, 2016	Meteorological	Heat wave	India still experienced extreme heat this year. In May, temperatures reached over 45°C in Telangana, Andhra Pradesh, Odisha and other states. Bhubaneswar saw a high of 47°C on April 26th as severe heat emerged earlier than normal ahead of the summer season. over 24 weather stations recorded temperatures higher than 45°C across different regions. In total over 300 deaths were officially reported during the 2016 heat season - lower but still considered substantial for loss of life. the Indian government launched national and state action plans along with an early heat-health warning system with advisory alerts to the public.
20th - 23rd June, 2016	Meteorological	Storm	Dust storms and thunderstorms with lightning strikes occurred in states like Uttar Pradesh, Bihar and Jharkhand, causing over 100 deaths. A severe storm with powerful winds battered Bengaluru city on June 23, uprooting trees and electrical poles, killing 2 people.
9th -31st July, 2016	Hydrological	Flood	The north-eastern state of Assam was hit by heavy monsoon rains, leading to widespread flooding. Over 5.7 million people were affected across 21 districts. At least 77 people died in the floods according to state government reports.
21st -29th August, 2016	Hydrological	Flood	Excess monsoon rainfall led to major flooding in states like Madhya Pradesh, Rajasthan, Uttar Pradesh and Bihar. Over 100 people reportedly died and affecting more than 3000 household due to drowning and collapsing infrastructures.
30 Oct- 11 Nov, 2016	Hydrological	Flood	Heavy rainfall and floods in states like Odisha, Andhra Pradesh, Telangana and Karnataka leading to over 325 deaths, affecting 1.8 million people and household. The floods of Odisha in October 1999 stands out as one of the worst surpass in this period.

25th January, 2017	Geological	Avalanche	Avalanches triggered by heavy snowfall mostly affected Jammu and Kashmir and Himachal Pradesh in January 2017. Over 20 deaths were reported, mostly soldiers and civilians buried under sliding snow.
Mid-May-Mid-June, 2017	Meteorological	Heat wave	Major cities like Delhi, Lucknow, Nagpur, Hyderabad, etc recorded temperatures above 44°C leaving millions impacted. Over 300 people died due to heat-related causes like dehydration, heat stroke, etc. Many cases were reported of roads and car tyres melting due to extreme heat. It was one of the hottest summers in over a century with temperatures breaking 50°C in some northern and central areas.
25th - 30th June	Hydrological	Flood	States like Assam, Arunachal Pradesh, West Bengal, Gujarat, Maharashtra and Madhya Pradesh were badly affected by floods. This led to extensive devastation and over 150 deaths and over 2.2 million people as per news reports documenting this natural disaster.
11th - 31st August	Hydrological	Flood	Severe floods brought death and destruction across the states of Assam, Bihar and UP through much of August 2017 - killing over 750 people and impacting millions as per news reports documenting this recurring natural disaster. Recovery and rehabilitation efforts went on for months.
11th July, 2017	Geological	Landslide	Continuous heavy rainfall has triggered widespread landslides in India's north-eastern states; Arunachal Pradesh, Meghalaya, Nagaland and Manipur leading to at least 46 confirmed deaths, blockade of transportation routes, damage to over 100 homes, and disruption to tourism and daily life.
2nd Dec, 2017	Meteorological	Cyclone Ockhi	Cyclone Ockhi that made landfall in southern India. The worst affected areas were Kanyakumari, Thiruvananthapuram and Tuticorin where heavy rains led to flooding. As per official records, Ockhi left over 245 people dead of whom around 220 were fishermen who had ventured out fishing in the Arabian Sea, and economic damage of $120 million in Kerala and Tamil Nadu.
1st – 7th January, 2018	Meteorological	Cold wave	North and Central India experienced an intense cold wave spell, Temperatures dropped much below normal. As per reports, over 120 people died due to related causes across these states such as hypothermia and illnesses. Both the government and NGOs set up emergency night shelters while distributing blankets to the underprivileged.
9th – 17th May, 2018	Meteorological	Storm	Dust storm in Rajasthan and Uttar Pradesh, Lightning Strikes in Bihar, Jharkhand, Andhra Pradesh, West Bengal and Tripura. As per report, 70 people died due to house/tree collapses, lightning and accidents caused due to severed power lines. And Affecting morthan 10000 people and Household.
23rd – 26th June, 2018	Hydrological	Flood	The arrival of monsoon rains brought a flood crisis to India in June 2018, causing immense damage in Assam while wreaking havoc across Manipur, Tripura, Kerala among other states - resulting in 52 deaths and displacing millions.
26th -28th July	Hydrological	Flood	One of the worst floods in Kerala in nearly a century occurred in July 2018. Over 300 people died and over 5 million were displaced by the devastating floods all across Kerala. Heavy rains led to dams overflowing and widespread destruction.

10th -17th August	Hydrological	Flood	The state of Kerala experienced devastating floods. All 14 districts of Kerala were placed on red alert as heavy rains led to flooding and landslides. Over 483 people lost their lives and over a million people were displaced from their homes. Emergency declared, relief and rehabilitation efforts continued for months
11th – 12th October, 2018	Meteorological	Cyclone Tilti	Cyclone Titli wreaked havoc as it made landfall in coastal region, killing over 100 people and leaving lakhs homeless due to its strong winds and torrential rains. National Disaster Response Force (NDRF) and state agencies action force act on as lakhs were displaced from their homes. Estimated damage from the cyclone was over USD $2 billion
16th November, 2018	Meteorological	Cyclone Gaja	Cyclone Gaja was a severe storm that caused significant damage, bringing heavy rains and winds. Caused over 80 deaths and widespread damage to infrastructure, crops, livestock. Over 1.7 million people evacuated by government authorities before the storm
5th May, 2019	Meteorological	Cyclone Fani	Made landfall in Odisha, causing storm surges and destructive winds up to 200 km/hr. Considered the worst cyclone to hit Odisha in 20 years. Over 16 million people across Odisha and Andhra Pradesh evacuated by authorities. Caused 89 confirmed deaths and major infrastructure damage, affected lives and livelihoods of more than 28 million people across 3 States in India.
June, 2019	Meteorological	Heat wave	A severe heatwave gripped large parts of India, with temperatures reaching over 50°C in some places. Rajasthan, Madhya Pradesh, Haryana, Punjab, Uttar Pradesh and Delhi were among the worst affected states. Churu in Rajasthan recorded the highest temperature of 50.8°C on June 2nd, 2019. over 200 potential heat-related fatalities were registered by early June. Schools and colleges changed their schedules to protect children and youth from exposure
1st- 7th July	Hydrological	Flood	The simultaneous large-scale flooding in Assam and Bihar highlighted the need for stronger flood readiness and response to minimize loss of life and economic costs. The death toll in both the state crossed 230, with 4.8 million people directly impacted
12th -18th August, 2019	Hydrological	Flood	The August flooding highlighted the vulnerability of states like Maharashtra and Karnataka to extreme rainfall during the monsoon season. Worst affected were Belagavi, Bagalkot, Vijayapura, Chikkodi, Shivamogga in Karnataka state. Over 3.4 million people were displaced and moved to government run relief camps. Shortage of essential supplies was an issue in cut-off settlements
29-4th December, 2019	Hydrological	Flood	The northeast monsoon brought heavy rainfall over in Tamil Nadu and Andhra Pradesh. Over 500 huts and homes in urban slum areas were fully damaged. There was disruption to road traffic, public transport, flights. 27 confirm death were recorded in rain-related incidents. Affecting 1.3 million people.
20th May, 2020	Meteorological	Cyclone Amphan	Cyclone Amphan was one of strongest storms over Bay of Bengal causing large scale human and economic losses underscoring India's vulnerability to climate change driven extreme weather events. Over 5 million people evacuated in West Bengal and Odisha before landfall.13 million people affected and at least 90 deaths confirmed across India and Bangladesh

10th -16th June, 2020	Hydrological	Flood	Assam faced early floods right from late May continuing through June, while Cyclone Nisarga also caused flooding around its landfall time near Alibaug, Maharashtra, highlighting India's tropical climate risks. By mid-June, flood waters submerged nearly 2,251 villages across 26 districts. 13 million people affected and at least 1922 deaths confirmed.
7th August, 2020	Geological	Landslide	Heavy rainfall triggered a major landslide in the Idukki district of Kerala. 33 death confirmed and at least 70 people were feared dead after landslide debris engulfed their quarters. Rescue teams had a tough time reaching the remote hilly location. Roads leading to the settlement suffered heavy damage.
13th -16th October, 2020	Hydrological	Flood	Heavy rainfall lashed Hyderabad and other parts of Telangana. Hyderabad received highest 24-hour October rainfall in over 100 years. Over 70 lives were lost due to flooding across Telangana. Thousands of vehicles and properties suffered damage. Water logging led to massive traffic jams, disruption in city. Power supply was suspended. Relief camps had to be opened to provide temporary shelter and aid.
7th -8th February, 2021	Climatological	Glacier outburst	The incident occurred at Joshimath in Chamoli along Rishi Ganga river, This led to dangerous flooding along the Rishiganga and Dhauli Ganga rivers. At least 31 bodies were recovered, 197 people declared dead or missing. Over 200 people lost their homes, livelihoods destroyed.
14th -19th May, 2021	Meteorological	Cyclone Tauktae	Made landfall on May 17th in Gujarat near Union Territory of Daman with wind speeds of 160 km/hr. The highest numbers of evacuations took place in Gujarat with over 2 lakh people evacuated. Estimated over 90 lives were lost across affected states with many on offshore facilities. Over 16,000 houses were damaged along with 33,000 hectares of cropland.
June, 2021	Hydrological	Flood	Maharashtra were described as the worst in decades for the state. Coastal and inland districts like Raigad, Ratnagiri, Kolhapur, Sangli witnessed flooding. 200 people died across flooded districts of Maharashtra. Thousands were evacuated and moved to relief shelters. Landslides compounded the flood damage across hilly areas
17th -18th July, 2021	Geological	Landslide	Torrential monsoon rains have triggered devastating landslides and floods in Mahad in Raigad district, Maharashtra located on the western coast of India. As per media reports, at least 33 fatalities have occurred due to rain-induced landslides and flooding across the city with rescue operations to locate missing persons trapped under debris.
11th August, 2021	Geological	Landslide	States with hill districts; Kerala, Himachal Pradesh, Uttarakhand, Assam triggered by heavy rainfall cause landslide. 33 confirmed death recorded. Number of people impacted due to road block and railway block.
26th -29th September 2021	Meteorological	Cyclone Gulab	A rapidly intensified cyclone made landfall in Andhra Pradesh on 26 September. Affecting Odisha and Andhra Pradesh and brought very heavy rains and winds gusting up to 95 kmph in coastal areas. 20 people lost their lives across rain and flood-related incidents. Over 100 villages flooded forcing evacuation of nearly 60,000 people in total. Thousands of hectares of standing crops damaged in the region

11th -20th October, 2021	Hydrological	Landslide/Flood	Torrential rain led to landslides in eight districts: Pauri Garhwal, Chamoli, Nainital, Almora, Champawat, Uttarkashi, Pithoragarh, and Udham Singh Nagar, while floods have affected a total of 13 districts. The incidents have resulted in 27 deaths. Rescue operations by the NDRF, SDRF, police, military, and Indian Air Force helicopters have saved or evacuated over 600 individuals. In Kerala, heavy rains have caused a rise in fatalities, with the Chief Minister Pinarayi Vijayan reporting 42 dead and 6 missing from October 12 to October 20.
18th -19th November, 2021	Hydrological	Flood	In Andhra Pradesh, floods from heavy rain, river overflow, and dam failure resulted in 32 deaths and 30 missing persons, with about 58,000 evacuated to shelters and over 74,500 affected in four districts, damaging around 3,700 homes.
April, 2022	Meteorological	Heat wave	The hottest summer in 122 years struck India's north, west, and central regions according to the Indian Meteorological Department, with notable impacts on Bhopal, Lucknow, Jaipur, New Delhi, Patna, Mumbai, Kolkata, Hyderabad, and Chennai. The region's peak temperature reached 45°C, resulting to 25 heat-wave related fatalities.
10 -19th April, 2022	Meteorological	Storm	The north-eastern state has been hit by persistent heavy rain, powerful winds, and thunderstorms, leading to flooding and severe incidents, especially from lightning. By April 19th, media reported 20 deaths primarily due to lightning, over 3,000 houses completely destroyed, about 19,000 houses partly damaged, and over 95,000 residents affected in 1,410 villages statewide.
17th – 26th May 2022	Hydrological	Flood	The situation with floods in Assam intensified the region, including India's Arunachal Pradesh, Nagaland, and Meghalaya states, as well as Bangladesh's Sylhet Division, with authorities reporting that over 400,000 people have been affected over 1,089 villages in 26 districts and killed 2035.
30nd June, 2022	Geological	Landslide	A massive landslide struck the Noney district of the Indian state of Manipur in the early morning hours. The landslide occurred near the Tupul railway construction site, killing 67 people by burying vehicles and structures, including 29 personnel of the Indian Army and 38 civilians. The landslide followed heavy rainfall over several days that had destabilized the hilly terrain.
23th -24th September, 2022	Hydrological	Flood	Heavy rainfall and thunderstorms were reported across northern India, resulting in at least 63 fatalities - 24 people died in Uttar Pradesh due to heavy rainfall-related accidents. Since June, the heavy monsoon rains have resulted in more than 1,945 deaths across India as reported by the National Emergency Response Centre (NDMI)

***Source**: Author's compilation from National Disaster Management Authority (NDMA) reports, National Disaster Response Force website and EM-DAT database*

5.2. Theoretical framework and hypothesis development

Examining the impact of natural disasters on stock price is a gaining ground from researchers in recent years. The impact of geological effects on disasters (Javid, 2007; Kong et al., 2021; Ruiz & Barrero, 2014; Sakariyahu et al., 2023; Scholtens; 2013) provides evidence on how this uncertainty event impacts the capital market. Stock markets are sensitive to occurrence with new information in the market, the same is true in climatology, meteorological and hydrological unwanted event that impact the normal life of the society as a whole resulting in economic uncertainty (Larcker et al., 2011). The impact on climatological change resulted in catastrophes in social and economic consequence has also received much attention (Alley et al., 2003; Bandh et al., 2021; Easterling et al., 2000; Feria-Domínguez et al..2020; Hayhoe et al. 2004; He et al., 2019; Matthews et al., 2017; Nordhaus & Yang 1996; Venturini, 2022). Hydrological calamities that jeopardise financial responses result in changes in investor sentiment and risk perception across certain regions, sectors, and companies (English et al.,2021; Czura & Klonner, 2023; Hallegatte, 2015; Liu et al.,2022; Nakata et al., 2018; Ramaiah, 2013).

For instance, disasters like natural disasters exuberate information uncertainty and are found more likely to impact the market in accordance with the event (Ferreira & Karali, 2015; Shan & Gong, 2017; Worthington & Valadkhani, 2004). Moreover, earlier existing literatures suggest that economic unimportant events show a significant impact on stock movement such as, cloud clever (Saunders, 1993), daylight (Kamstra et al., 2000:2003), sunshine (Hirshleifer & Shumway 2003), temperature (Cao & Wei, 2005). The impact of an uncertain event that induces investor sentiment in the market due to the Covid-19 pandemic is found to be true in the global market. Individual responses to the market lead to information pricing. Natural disasters have varying impacts on investors, including exuberating information asymmetry and risk overestimation (Alok et al., 2020). The impact on this matter can be ascertained from two theoretical perspectives: pricing of information or efficient market movement (Fama, 1965; Malkiel, 1962), or the reaction of information amongst the participant or a behavioural perspective (Subramanyam, 2008).

5.2.1. Investor Sentiment and natural calamities

5.2.1.1. Studies on Geophysical effect

According to a previous study, despite the likelihood of low occurrence, people pay undue attention to events that cause substantial losses. One of the geophysical natural disasters is earthquake, which have a significant impact on the stock market, but the nature of this impact varies. Scholtens and Voorhorst (2013) found earthquakes have a negative effect on stock market value, with more pronounced effects in recent years. Javid (2007) examines the specific case of the 2005 earthquake in Pakistan and finds both positive and negative effects on stock prices and activities. Yong-gang (2011) focuses on the 2008 Sichuan earthquake in China and concludes that while there was a short-term impact on the stock market, the long-term impact was limited. Wang et al. (2012) studies the influence of the Japanese earthquake on global stock markets and identifies different effects on different stock indices. Earthquakes tend to cluster in specific places with active geological activity. People overestimate the risk and exhibit risk aversion as a result of the salience of the adverse effects (Slovic et al., 1997; Bordalo et al., 2012). People exaggerate the impact of the event on their decision-making process and reflect uncertainties and threats of such an occurrence in their feelings of fear, dread, and anxiety (Loewenstein et al., 2001). The study by Mishra et al. (2021) highlights those geological calamities, such as landslide, tend to have a significant negative impact on the stock performance of major companies across various industries in Indian stock market, However, the authors also found that when relief programs or government interventions are announced in the aftermath of these events, the market responds positively, resulting in a normal return for the affected companies.

Natural disaster would possibly destroy the physical nature of production at least for a short span of time (De-Mel et al., 2012; Kahn 2005). This would indirectly hamper the firm operation after the natural disaster. Worthington and Valadkhani (2004) conducted a study on impact of natural disasters in Australian equity market found earthquake has major impact on stock market as compared to other natural disaster like storm and floods. Shelor et al. (1992) examine the aftermath of 1982 California earthquake in the insurer stock value, they found insurers' stock rises following the earthquake due to increased demand, rather than falling due to increased coverage payments. Ruiz and Barrero (2014) investigated the impact of the 2010 Chilean earthquake in stock price and volatility in the Chilean stock market using event study approaches. They found a positive return in retails, real estate and banking sector during this natural calamity. The stock volatility shows a tremendous increased by 240 percent during the five trading days after the earthquake shock. Halim and Zen (2017) also found that stock probe to disaster emergency handling like consumer goods and infrastructure sector have significant direct impact on abnormal return from day 0 till day 10. Kong et al. (2021) conducted an empirical investigation into the effects of seismic events on firm performance in Chinese capital markets. Their findings revealed no statistically significant impact on corporate earnings or equity returns following such natural disasters, which aligns with previous finding by Ferreira and Karali (2015). These indicate that post-earthquake pessimism is not based on rational judgement.

Bourdeau-Brien and Kryzanowski (2017) documented major natural disasters often increase risk aversion and induce abnormal stock returns and volatilities. Similar finding was found in Turkey-Syria earthquake (Sakariyahu et al., 2023). The study revealed a significant negative correlation between the earthquake disaster and stock market returns in countries with strong economic ties to Turkey. This relationship was found to be statistically significant at the 1% level, indicating a pronounced impact on investors in these interconnected markets. An event study approaches using 42 listed companies in Santiago stock exchanges was conducted by Ruiz, (2010). He found that stock market volatility reached a spike of 240 percent in the earthquake catastrophes during the post five trading days and higher positive return was found in real estate, retails and banking sector. This claims that sentiment on stock due to natural disaster could be one of the factors that influence the behavior of the stock. This is aligned with the finding of Hood et al. (2013) that natural disaster affects the trading behavior. Based on the earlier literature, the economic impacts of disasters on capital market, especially on developing economies, remain inadequately explored and theorized. Recent research has shed more light on the complex relationship between natural hazards and economic performance in advance countries and no significant focus was conducted in India, advancing this study will enhance the existing literature on how sentiment on natural disaster influencing the behavior of the stock. Here are some potential hypotheses that are formulated for this study on the economic impacts of natural disasters on the capital markets in India:

H_{5a}: Natural calamities have a significant negative impact on stock market return

5.2.1.2. Studies on hydrological effect

Natural calamities in term of flood and tsunami are among the most severe shock that jeopardizing the finance response in the countries. Thus, the hydrological effects of natural calamity have a significant negative impact on economies and human life, causing long-term and short-term economic impact (Mata-Lima et al., 2013) resulting in direct crop loss, (Brown et al, 2011) reduce in sale of agricultural input (English et al.,2021), as well as lower productivity, disruption of trade and supply chain and loss of income in the long run (Hallegatte, 2015). Moreover, the floods have a significant impact on firm performance that alter firm policies and affects the economic growths (Pan & Qiu, 2015). Czura and Klonner (2023) conducted an aftermath 2004 Indian ocean effect and concluded that natural disaster affect individual with substantial heterogeneity. The investment in household stocks are significantly lower during the natural hazard moreover house hold with low financial literacy tend to be more risk averse during this unwanted natural disaster events. The results are in support of prior finding (Liu et al., 2022). Earlier literature De Mel et al. (2012) and Deryugina et al. (2012) also highlights that small and medium enterprises (SMEs) tend to be more severely impacted by flood damage compared to other households in the aftermath of major flood events like the 2004 Indian Ocean tsunami and Hurricane Katrina.

Hydrological disasters can shape investor sentiment and risk perception towards certain regions, sectors, or companies. Nakata et al. (2014) showed that the 2011 Thailand floods led to a decline in investor sentiment, as reflected in lower trading volumes and increased risk aversion. Malik et al. (2020) conducted a study examining the market response to domestic natural disasters in the United States over a period of 45 years. One notable finding from the study is that the gold industry consistently exhibited materially large abnormal returns of 3.31 percent over the 30-

day post-disaster period following hydrological disasters. This observation suggests that investors may perceive gold as a safe-haven asset during times of natural calamities, leading to increased investment in the gold industry and driving up its returns. Reddy and Mallesha (2021) further claimed that natural disaster on floods cause a major impact on the state economy, risk of banks failure in the regions, however they claimed disaster is not always sensitive to this event in the stock market and performance of stock return. Ramaiah (2013) conducted an event study to assess the impact of the tsunami on financial markets using CAPM (Capital Asset Pricing Model). He highlighted an overall increase in long-term market risk across 13 industry portfolios in stock exchange of 43 countries. According to the analysis, the stock market reacted almost insensitively or nonexistence to this event. Based on the literature provided, a relevant research question is how do hydrological disasters, such as floods and tsunamis, impact investor sentiment? and how investor reaction in stock market across different industries may be addressed. To address this research question, the following hypotheses could be formulated:

H_{5b}: Hydrological disasters have substantial adverse effects on stock returns, particularly for firms and industries that are directly affected or dependent on natural resources

5.2.1.3. Studies on Meteorological effect

The consequence of climate shock and climate change is visible on a daily basis across the globe. The Task Force on Climate-Related Financial Disclosures (TCFD), established by the Financial Stability Board (FSB), has developed recommendations for companies to disclose climate-related risks and opportunities (TCFD, 2017). The TCFD's recommendations aim to improve the availability and quality of climate-related financial information, enabling better-informed investment, credit, and insurance underwriting decisions. According to Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Change and Land[5], Climate change has already led to an increase in the frequency of water stress and this trend is expected to continue in some arid region (Hoegh-Guldberg, 2018). Hong et al. (2019) by conducting a seminal work to evaluate economical and financial impact of drought,

[5] https://www.ipcc.ch/sr15/chapter/chapter-3/

found that drought have a significant negative impact on the profitability of food companies. They further conducted a long and short positioning of portfolio of food companies in a country experiencing drought region and not effected countries, such portfolio generated an annualized return of 7 percent. Drought intensity is positively and significantly associated with the ex-ante cost of equity implied in stock price, Huynh et al., (2020) provide evidence that firms are affected by severe drought condition by 92 basis point that lost cannot be minimized by diversifying strategy. There is a casual effect on drought intensity, drought duration and firm risk premium. Hillier et al. (2006) focused specifically on the effect of droughts on the financial performance of agricultural firms. Their research showed that droughts can lead to significant declines in crop yields, which in turn negatively affects the profitability and stock returns of agri-food companies. The study also found that the impact is more severe for firms dealing with perishable products, as they have limited ability to store or preserve their products during periods of drought. Cheng et al. (2022) study the effect of drought on stock price using OLS and quantile regression. The OLS regression shows a decrease in industry stock price due to drought. However, a negative and positive effect was found using quantile regression from highly effect in real estate and to least effect in financial services sector stock return. Feria-Domínguez et al. (2020) conducted a study the drought announcement effect in IBOVESPA stock market adopting an event study method, taking event window of 5, 20, and 40 days. The findings suggest that the announcement of droughts in Brazil had a negative impact on investor sentiment, particularly for companies dealing with perishable agricultural and food products. The sentiment impact was more pronounced for these firms compared to those involved with non-perishable products in the Brazilian agri-food sector.

Examining the impact of natural disaster on stock price is a gaining ground from researcher in recent years. Cao et al. (2015) conducted a study on how significant meteorological effects have on the Chinese and US stock markets, emphasizing the importance of understanding sectoral sensitivity to such events. The result suggest that domestic disaster have a significant impact on the host countries as compare to that of foreign events. Further, they claimed that climatic event can affect various industries differently, and different climatic events can have varying effects on the same industry in China. They provided significant evidence; the snow storm in China in 2008 significantly impacted more industries compared to the snow storm in the USA in 2006. Moreover, Gillingham et al. (2018) documented that companies engaged in carbon-intensive are more vulnerable in to the impact of meteorological disaster as compared to renewable energy sector. Further, Gillingham et al. (2018) documented that the announcement of climate policies had a substantial effect on the stock prices of companies operating in carbon-intensive sectors. This implies that sentiment plays an important role in the performance of the stock prices. Symeonidis et al. (2010) investigated the relationship between stock market volatility and weather-related factors like cloudiness, temperature, precipitation, and environmental factors such as nighttime length. The findings indicate cloudiness and night length negatively correlated with historical, implied, and realized volatility measures in stock markets. The association between these factors and volatility differed across different exchange location and weather deviations from seasonal norms and extreme weather conditions did not significantly impact stock market volatility. Kruttli et al. (2023) developed a framework to comprehend how stock markets react to the extreme weather events and their economic consequences. The study concentrated on stock options of firms located in regions prone to hurricane landfalls. The researchers discovered that implied volatility exhibited a significant increase due to the uncertainties surrounding the occurrence and economic impact of these extreme weather events. The study revealed a positive association between heightened idiosyncratic volatility and expected stock returns. Venturini (2022) in his systematic literature review critically examined the impact of climate change as an additional source of market risk on equity markets. The study highlighted the role of investors' perceptions and beliefs regarding climate change risks, affecting asset pricing. In this context developing a disaster sentiment is crucial. The development of a disaster sentiment-based index can capture investor perceptions and beliefs regarding climate change risks and extreme weather events, allowing for better understanding and pricing of these risks in financial markets. Based on the literature review provided, the following hypotheses can be formulated to develop a disaster sentiment-based index:

H_{5c}: Climate-related disasters and extreme weather events have a significant negative impact on the stock returns

The literature on the impact of natural disasters on stock markets varies. The existing literature presents diverse findings regarding the effects of natural disasters on stock market performance. Empirical studies have yielded mixed results, with some researchers reporting significant negative impacts, while others observe minimal or short-lived effects. Factors such as the type and severity of the disaster, the economic resilience of the affected region, and the specific sectors involved contribute to the heterogeneity of outcomes. Various studies claimed disaster events provides a significant negative impact on stock return performance, however some studies claimed that the market are insensitive. Few studies have been conducted in the Indian stock market was quite scanty. This highlights that further investigation is needed to assess how natural disaster events affect the stock market, especially given the rising frequency and severity of such occurrences in India. Furthermore, to the best of our knowledge, no studies have developed a sentiment based on the natural disaster index, allowing a framework to study the relationship between natural disaster sentiment and stock prices. This study offers insightful perspectives on the intricate relationship between natural disaster events and the dynamics of financial markets, thereby enriching the existing body of knowledge in this domain. By elucidating the complex interplay between environmental phenomena and capital market performance, this research endeavour makes a significant contribution to the extant literature, advancing our collective understanding of this critically important area of inquiry.

5.3. Data Specification

5.3.1. Data description

An assessment of the data requires the representation of the sample population with minimum bias and maximum adeptness. Weekly data are taken into consideration as events in terms of disasters, since disasters occur for uncertain periods; for instance, drought, floods, and extreme weather conditions took an extensive period of time, and records on specific dates were extensive longer than those of earthquakes or landslide disasters. The relative period of the event could best describe these events. Therefore, using daily data could result in an incorrect estimation depending on the type of disaster; for this reason, a weekly return series is considered desirable in the present study. A monthly period return is also a cause of concern because there could be a wide range of factors, and dynamic market conditions influence the stock market during the whole period of the month.

5.3.1. Data

For this set of data, the closing price of Bombay stock exchange (BSE) sectoral data was taken from the official website from 1 January 2013 to 31 December 2022. The BSE sectoral indices have 20 sectoral indices, of which the S&P BSE service sector was left insignificant to the study due to incomplete data sample for the study period. The study selected 19 sectoral equity indices in the BSE: Auto, Bankex, Consumer Durables, Capital Goods, Fast moving consumer goods, Telecommunication, Utilities, Commodities, Consumer Discretionary, Energy, Financial, Industrials, Healthcare, information technology, Metal, Oil & Gas, Power, Realty, and Teck. The initial motive was to identify which sectors that impact natural calamities.

5.3.2. Estimation of excess return using market adjusted return model

According to the literature on event studies, one of the most commonly used models is the Market Model, which explicitly accounts for any risk associated with the market and its mean returns (Arora, 2001; Jung et al., 1992; Schipper & Thompson, 1983). A major advantage of using this model over others is that it is error-proof and avoids the extra computations associated with estimating security betas. The model uses the well-known Capital Asset Pricing Model (CAPM) assumption, which essentially assumes that the expected returns of a security are equal to the market return. This implies that while the expected return is constant across securities, it is not constant across time, with α and β set equal to 0 and 1, respectively. The aforementioned advantages of the Market Model led to its selection for calculating the abnormal returns in this study. The market-adjusted model assumes the expected return to be equal to the market return (Arora, 2001; Jung et al., 1992; Schipper & Thompson, 1983). The abnormal returns (excess returns) are calculated by subtracting β of the individual sectoral indices multiplied by market returns in our case, Sensex 30, from the weekly stock returns. This can be expressed using the following equation:

$$R_t = Abnormal\ Return = R_{w,t} - \beta R_{M,w,i,t}$$

Where, R_t is the abnormal return or excess return of sectoral indices. $R_{w,i,t}$ is the weekly return of sectoral return i at time t, $R_{M,w}$ the weekly market return for Sensex and β is a systematic risk calculated by dividing the covariance of the sectoral returns and the markets returns with the variance of Sensex index return. The approach outlined by Bijl et al. (2016), where we utilize the opening price of the first trading day of the week as our reference point. The rationale behind this choice is that the opening price represents the earliest opportunity for market participants to react to new information released during the preceding weekend, specifically the weekly Google Search Volume Index (GSVI) data, which is reported from Sunday to Saturday. Our decision to employ weekly data is driven by the availability of an extensive historical dataset spanning multiple years, enabling us to conduct a comprehensive analysis over an extended period.

The descriptive statistics provided in Table 5.2 offer insights into the stock index returns and sectoral index returns. The mean excess returns are positive across all sectors, with the Industrial sector exhibiting the highest mean return and the Telecommunication sector displaying the lowest. The standard deviation, a measure of volatility, reveals that the Realty sector has the highest level of volatility among all sectors, while the Telecommunication sector exhibits the lowest return volatility. Interestingly, the market index displays lower volatility compared to all the individual sectors. An examination of skewness reveals that nine sectors and the market index have negative skewness, indicating that the returns are skewed towards the left side of the normal distribution curve. Conversely, positive skewness is observed in 10 sectors, suggesting a rightward skewness in the distribution of returns. The Jarque-Bera (JB) test, a goodness-of-fit test for normality, indicates that the daily distribution of returns deviates significantly from the normal distribution, as evidenced by the non-zero values. This suggests that the excess returns are not normally distributed. Furthermore, the kurtosis values indicate that the returns have a sharp peak with a leptokurtic distribution, implying a non-normal distribution and a tendency towards higher risk. The Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin

(KPSS) unit root test, used to assess stationarity, suggests that all the data series are stationary at the first level of difference, meaning that the time series are stationary after taking the first difference. The total number of observations in the dataset is 528 observations.

Table 5.2: Descriptive statistics of sectoral indices

Sectoral Indices	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Obs
Auto	0.055	0.695	1.267	19.908	7076.41*	-22.68*	0.078	528
Bankex	0.067	0.738	0.093	9.849	1136.27*	-23.50*	0.028	528
Capital Goods	0.060	0.719	-0.017	4.387	46.65*	-14.46*	0.094	528
Commodities	0.067	0.665	0.026	5.743	182.24*	-20.99*	0.087	528
Consumer discrepancies	0.057	0.484	-0.377	3.606	22.67*	-21.09*	0.098	528
Consumer Durables	0.070	0.649	-0.263	6.289	268.61*	-22.12*	0.045	528
Energy	0.059	0.659	-0.529	9.386	1014.27*	-15.06*	0.056	528
Financial Services	0.064	0.681	0.028	9.614	1059.21*	-22.93*	0.029	528
FMCG	0.056	0.483	0.048	6.451	288.44*	-13.61*	0.032	528
Healthcare	0.059	0.515	1.471	22.887	9784.19*	-13.21*	0.160	528
Industrial	0.072	0.674	-0.193	4.684	72.33*	-20.02*	0.121	528
Information Technology	0.058	0.614	-0.659	6.613	358.18*	-8.22*	0.084	528
Metal	0.041	0.861	0.052	4.729	72.63*	-14.89*	0.150	528
Oil & Gas	0.043	0.641	-0.753	11.538	1820.12*	-22.81*	0.047	528
Power	0.047	0.662	0.018	5.205	117.75*	-14.16*	0.268	528
Realty	0.049	0.956	0.049	4.593	61.69*	-21.55*	0.094	528
TECK	0.050	0.156	-0.318	2.074	30.54*	-7.15*	0.013	528
Telecommunication	0.026	0.447	0.430	8.134	656.04*	-7.23	0.178	528
Utilities	0.039	0.212	-0.164	2.532	7.89**	-8.20*	0.091	528
Market index	0.005	0.015	-0.393	2.808	10.11*	-6.21*	0.024	528

***Source**: Author's Computation using EViews*

Note(s): The descriptive statistic also includes examining a significant preliminary requirement for the use of examine the empirical approach.

*, **, *** denotes significant at 1%, 5% and 10% respectively.

5.3.3. Classification of natural calamities

The following dataset is an uncommon database in economics that contains data related to natural disasters: This is the Emergency event database or the international disaster database commonly known as ED-DAT. This database was developed by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain in Belgium in 1988. This was a joint effort between the World Health Organization (WHO) and the government of Belgium. The data has been collected from multiple sources, including UN agencies, national institute of disaster management, insurance companies, research institutions, and other non-governmental organizations. The Emergency Events Database (EM-DAT) has established specific criteria for natural disasters to be included in its database. To qualify for inclusion as a natural disaster, an event must meet at least one of the following three conditions: first, it must have caused a minimum of ten or more fatalities; second, it must have affected at least 1000 individuals; and third, a state of emergency must have been declared, prompting a call for international assistance. The different categories of events that met the EM-DAT criteria for inclusion as natural disasters were earthquakes, avalanches, floods, droughts, heat waves, cold waves, cyclones, landslides, and snow bursts. This comprehensive list encompasses a wide range of catastrophic events, each with unique characteristics and potential for devastating impacts on communities and regions across India.

5.3.4. Natural calamities events

The research concentrates specifically on natural disasters, which are calamities triggered by geophysical, hydrological, climatological or meteorological phenomena. It is essential to acknowledge two significant caveats associated with the EM-DAT (Emergency Events Database) utilised in this study. Firstly, the database only accounts for the number of individuals who lost their lives during the immediate aftermath of the disaster event itself. Secondly, the database fails to capture the indirect impact on populations residing far from the disaster's epicenter, who may have experienced disruptions in economic activities or fluctuations in prices due to the event's ripple effects.

To address these limitations and ensure comprehensive information, the research incorporates reports from the National Disaster Management Authority. These reports provide a more robust and inclusive assessment of the disasters under consideration. By triangulating data from the EM-DAT database with the National Disaster Management Authority reports, the research aims to present a more accurate and complete picture of the natural disasters, their consequences, and the extent of their impact on affected regions and populations. India experienced 112 natural disasters out of which 60 natural disasters fulfilled the disaster as defined by the database between 1 January 2013, and 31 December 2022 (See table 5.1). It is noteworthy that in some instances, a single natural disaster may have affected multiple states, in which case it is considered no distinct event for each affected state and consider it as one natural calamities event.

Table 5.3: Descriptive statistic of natural disaster effect

	Mean		Volatility			
	Natural Disaster	**Non-Natural disaster**	**Natural Disaster**	**Non-Natural disaster**	**t-stat**	**KS-Stat**
Auto	0.441	0.111	0.713	0.594	-0.871	0.061
Bankex	0.065	0.077	0.756	0.646	-0.150	0.064
Capital Goods	0.096	0.052	0.642	0.734	-0.549	0.067
Commodities	0.093	0.062	0.585	0.680	-0.421	0.076
Consumer discrepancies	0.075	0.054	0.474	0.486	-0.392	0.066
Consumer Durables	0.127	0.057	0.625	0.653	-0.962	0.152**
Energy	0.149	0.041	0.559	0.676	-1.480**	0.104
Financial Services	0.075	0.061	0.596	0.698	-0.181	0.061
FMCG	0.027	0.061	0.518	0.475	0.636	0.099
Healthcare	0.073	0.056	0.451	0.527	-0.300	0.064
Industrial	0.099	0.065	0.588	0.690	-0.448	0.074
Information Technology	0.046	0.059	0.553	0.626	0.191	0.126
Metal	0.112	0.026	0.830	0.867	-0.894	0.104
Oil & Gas	0.121	0.027	0.532	0.660	-1.316***	0.096
Power	0.127	0.030	0.674	0.658	-1.330***	0.095
Realty	-0.034	0.066	0.825	0.980	0.941	0.111
TECK	0.073	0.045	0.130	0.160	-1.585**	0.142***
Telecommunication	0.018	0.027	0.427	0.451	0.167	0.084
Utilities	0.070	0.032	0.193	0.214	-1.608**	0.131
Market Index	0.072	0.0045	0.013	0.015	-1.535**	0.103

Source: Author's Computation using Stata

Note(s): KS= Two-sample Kolmogorov-Smirnov test for equality of distribution functions t-test = Two-sample t test with equal variances. The observation for natural disaster comprises of 90 observations and the non-natural disaster events comprise of 438 observations.

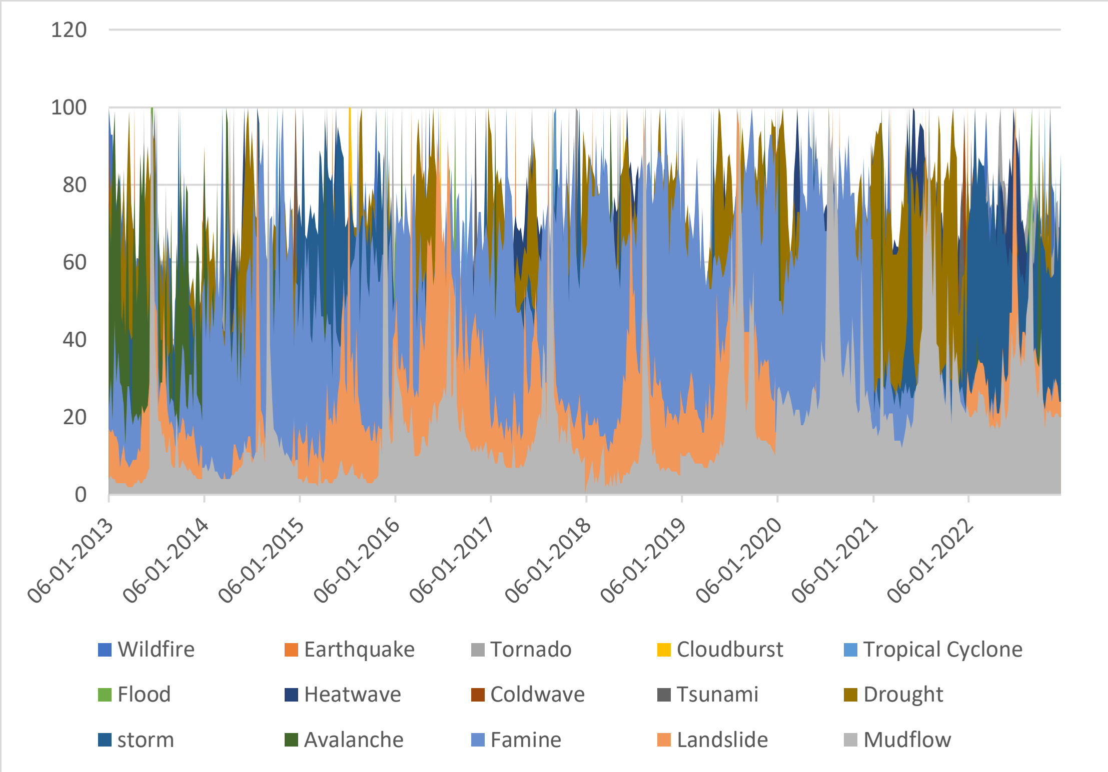
5.3.5. Sentiment analysis

The second stage of the study is to examine reaction of investor attention to natural disaster on the stock market. For this, a measure of investor sentiment needs to be examined, and we employ data on search volumes related to natural disasters.

Following Da et al. (2011, 2015), the present research assumed that sentiment related to natural disasters, as represented by Internet search behavior, can be considered a measure of sentiment. Market-level sentiment was, therefore, directly measured through weekly Internet search behaviour related to natural disasters. The underlying idea is that the search queries people make can reveal valuable information about their concerns, interests, and attitudes toward financial and economic matters. These studies demonstrate the continued interest and development in using internet search data as a proxy for investor sentiment and behavior, highlighting the relevance and potential applications of this approach. In line with an earlier approach (Da et al., 2015, Bijl et al., 2016, Subramaniam & Chakraborty, 2020), the underlying assumption is that an increase in search queries for these terms can indicate heightened public awareness, fear, or worry about the potential occurrence or impact of such events. By aggregating the volume of queries associated with natural disasters, the aim was to develop a Google-based Disaster sentiment index.

The Google search volume was restricted to only India using keywords related to natural disasters and weather events, such as "Earthquake," "Avalanches," "Cyclone," "Storm," "Flood," "Drought," "Heatwave," "Coldwave," "Landslide," “Wildfire”, “Tornado”, “Cloudburst”, “Tsunami”, “Mudflow”, and “Famine” from January 2013 to December 2022. The GSVI provided by google trends is an index, not a search volume in absolute term rather a metric that compares the number of searches on Google for a particular subject to the total number of searches in the same time period. GSV standardized the relative value within a range of 0-100, where GSVI value of 100 indicates the peak popularity for the search query and 0 indicates the lack of enough data for the search query. The graphical representation of GSV on natural disaster are shown in Figure 5.1.

Figure 5.1: Natural disaster related Google search volume



Source: Google search volume index

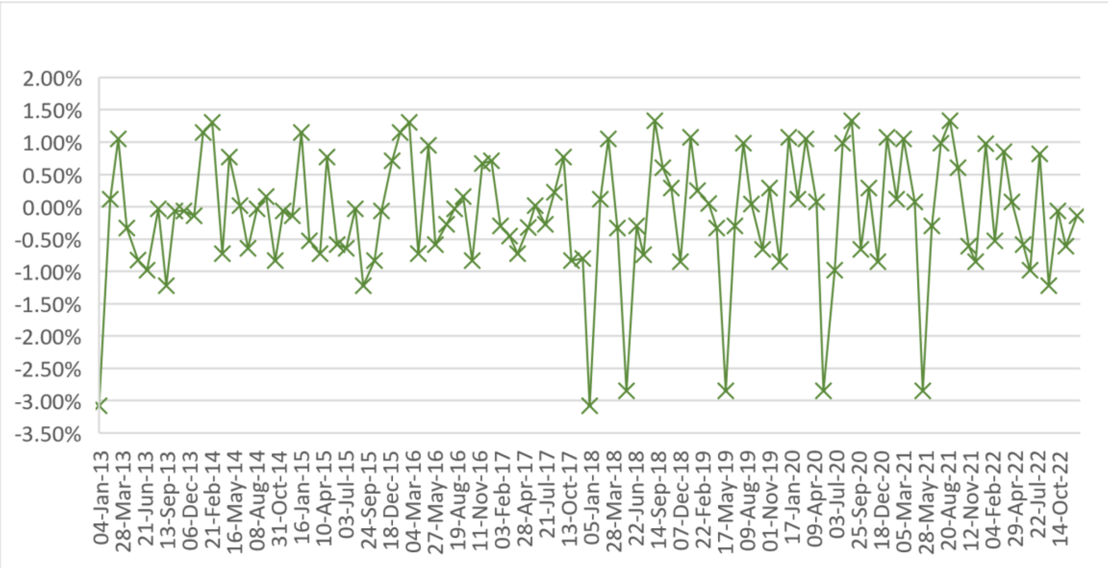
5.3.6. Construction of Disaster Sentiment Index

Since the data for the natural hazard is a periodic that occurred within a diminutive period of a year. Search volume on this natural data might varies on specific period. This might lead to a spurious result in the estimated output, moreover the estimated data is longer period required further adjustment for this observation (Bijl et al., 2016). To analyze the search trend dynamics, the logarithmic daily changes in these search volume indices were calculated. This transformation involves taking the natural logarithm of the ratio between the current weekly search volume index and the previous week value for each term. By computing the log changes, the analysis can focus on the relative variations and fluctuations in search interest over time, rather than the absolute search volume levels. This approach is commonly employed to mitigate the impact of potential non-stationarity and facilitates the examination of percentage changes in the search volumes (Subramaniam & Chakraborty, 2020). The weekly log change in the search term is estimated

$$\Delta GSVI_{i,t} = \ln\left(GSVI_{i,t}\right) - ln\left(GSVI_{i,t-1}\right)$$

Where $GSVI$ is the Google Search Volume Index. To further deal with data sets that exhibit different scales, magnitudes, or distributions and ensure the comparability of the final list of terms and address potential issues such as outliers, seasonality, and heteroscedasticity in the data. The log return is normalised in the range of [0,1], this will ensure that the data is properly scaled and transformed to meet the assumptions of statistical models. To construct the Disaster Sentiment Index, principal component analysis (PCA) was employed on the Google Search Volume Index (GSVI) data for various disaster-related keywords. The Disaster sentiment index depicted in Figure 5.2.

Figure 5.2: Disaster sentiment index



Source: Author's computation

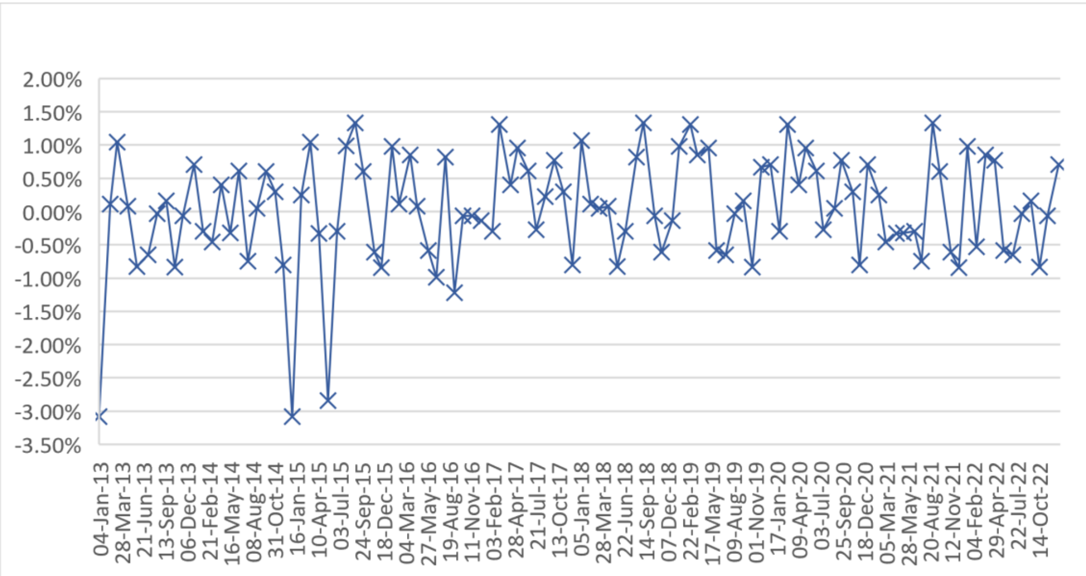
5.3.7. Control Variables

5.3.7.1. Market Mood index

The Market Mood Index (MMI) is a sentiment indicator constructed by ET NOW, capturing investor sentiment in the Indian stock market. This index is derived from data obtained from the tickertape website. MMI is widely disseminated to the public and aims to capture sentiment based on various market indicators through television, newspapers, and the internet. The index considers six key variables: foreign institutional investor (FII) activities, volatility and skewness, the difference between the 90-day and 30-day exponential moving averages of the Nifty index, market breadth, price strength, and demand for gold, providing a comprehensive understanding of market emotions. MMI is a standardized value ranging from 0 to 100 and is categorized into five variables. A value between 0 and 30 indicates extreme fear in the market, while a value between 30 and 50 indicates fear. A value around 50 is considered neutral. A value ranging from 50 to 70 indicates greed, and a value between 70 and 100 is considered extreme greed.

Aggarwal (2017) studied the influence of Indian market sentiment on stock returns, using MMI as a proxy for sentiment, suggesting a positive relationship between MMI and stock returns. Furthermore, MMI has a causal effect on stock returns during extreme phases, and higher sentiment tends to lower volatility (Chakraborty & Subramaniam, 2020). The plot of change in MMI is shown in figure 5.3.

Figure 5.3: Market mood index

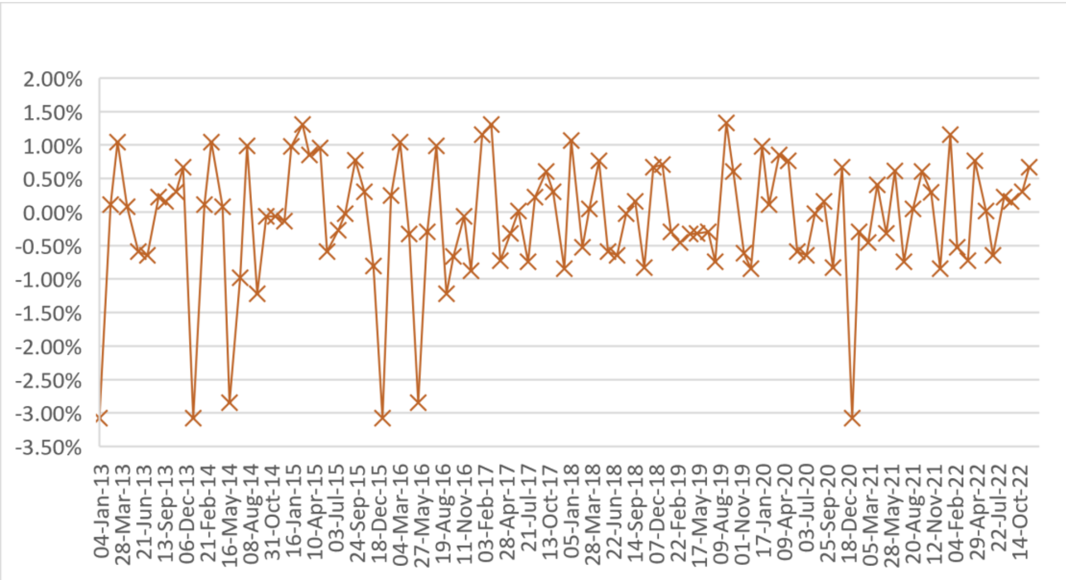


Source: https://www.tickertape.in/

5.3.7.2. VIX index

The VIX Index, also known as the Fear Index or Fear Gauge, is a widely followed measure of expected volatility in the stock market. In India, the National Stock Exchange (NSE) calculates and publishes the India VIX, which is based on the computation methodology of the CBOE Volatility Index (VIX) used in the United States. The India VIX is widely used by traders, portfolio managers, and risk managers as a gauge of market sentiment and a tool for portfolio risk management. It serves as a barometer of fear in the market, with high VIX levels generally associated with periods of increased risk aversion and market turbulence. The India VIX is a real-time index that measures the market's expectation of 30-day volatility implied by Nifty Option prices. It is calculated using the order book of Nifty Options and provides a measure of the risk premium that investors are willing to pay for portfolio protection. A higher India VIX value indicates that investors expect greater volatility in the Nifty Index over the next 30 days, while a lower value suggests that the market anticipates relatively calm conditions. Historically, the India VIX has exhibited an inverse relationship with the Nifty Index, meaning that when the Nifty rises, the VIX tends to fall, and vice versa. The plot of change in VIX is shown in figure 5.4.

Figure 5.4: VIX Fear Index India



Source: https://www.nseindia.com/reports-indices-historical-vix

5.3.8 Descriptive statistic of Sentiment Index

Table 5.4 provide the descriptive statistics of independent variables for sentiment index stated and examine whether the statistical requirements are fulfilled for the empirical approaches. The order of integration and serial independence are fulfilled in constant not in a dynamic stable character. The unit root test was examined using Augmented Dickey Fuller test (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) suggests that all the data are stationary at the first level of difference. Moreover, none of the variables are of I (2). The Jarque-Bera (JB) test, a goodness-of-fit test for normality, indicates that the daily distribution of returns deviates significantly from the normal distribution. The data with not normal distribution can be ignored as per the central theorem in large sample (Ghasemi & Zahediasl, 2012). The correlation matrix provided in Table 5.5 show no serial correlation between DSI with VIX and MMI. There is significant negative relationship between MMI and VIX, a correlation value is less 0.3 which is considered relatively low, it does not necessarily preclude the inclusion of a variable in a multiple regression analysis (Kutner et al., 2005; Hair et al., 2010).

Table 5.4: Descriptive statistic of Sentiment Index

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	KPSS	Obs
DSI	0.010	1.010	1.237	9.910	110.54*	-15.94*	0.011	528
MMI	0.002	0.023	0.150	3.037	2.022	-12.70*	0.121	528
VIX	0.132	0.796	-0.39	3.76	18.49*	-6.96*	0.034	528

Source*: Author's Computation using Stata*

Note: * indicates significance at 1% level. The value is measured with the logarithmic and normalization transformation of the weekly sentiment data.

Table 5.5: Correlation test for the sentiment index				
		Correlation	t-Statistic	Probability
MMI	DSI	0.012044	-0.253300	0.8001
VIX	MMI	-0.277618	-5.543251	0.0001
VIX	DSI	-0.050621	0.953063	0.3412

Source*: Author's Computation using Stata*

5.4. Econometric Model

5.4.1. Identification of Econometric framework

This section outlines the model specification and the methods employed for analyzing the data. The choice of the econometric model requires to meet the research hypothesis and shape of the dataset. A natural disaster is a sudden event that occurs within a specified period, providing a low-dimensional summary of the dataset that captures the true signal of investor sentiment reaction toward the market, which can be called the "effect of natural disasters". To analyze this effect, parametric multivariate regression analysis using an ordinary least squares (OLS) model and a non-parametric approach using the Kruskal-Wallis (KW) test were employed.

To evaluate the natural disaster effects, this study estimated the linear regression as follow:

$$R_{it} = \alpha_i + \beta_i D_{it} + \epsilon_{it} \tag{5.1}$$

Where, R_{it} is the sectoral excess return of BSE sectors i at the week (t=, 1,…… T). D_{it} is the explanatory variables in our case a list of various natural disaster dummy (see Table 1 for the list). β_i is the coefficient for corresponding natural disaster effect. The null hypothesis (H_0) specifically focuses on the natural disaster coefficient β_i (H_0: β1 = 0 or H_1: β1 ≠ 0). ϵ_{it} is the error term, to account for potential heteroscedasticity and serial correlation in the error terms, the Newey-West estimator was employed for the error term. To avoid multicollinearity effect, an initial estimation was conducted using the overall natural disaster dummy, followed by impact of other Disaster on the sectoral return of the Bombay stock exchange that do not provide a multicollinear effect on those events.

Further, the Kruskal-Wallis (K-W) test was employed, as the OLS model does not adequately account for capturing the non-normality of the data. The Kruskal-Wallis (K-W) test was used to determine whether the samples drawn from different populations had the same distribution between the median groups. The Kruskal-Wallis test was used to detect disparities in the central values under comparison. It does not make assumptions about the normality of the data distribution, is not as strongly influenced by the presence of outliers, and is particularly sensitive to means (Urquhart & McGroarty, 2014; Khuntia & Pattanayak, 2022).

The K-W test in comparing a significant difference between sectoral index return on natural disaster events and non- disaster event were computed as follows:

$$KW = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j}\right) - 3N(N+1) \tag{5.2}$$

where R_j^2 represent the mean rank of observation in the j^{th} category. n_j corresponds to the total sample size in the j^{th} category. k denotes the number of group. The total number of observations is denoted by N. The Kruskal-Wallis estimate follows a chi-squared distribution with (K-1) degrees of freedom. If the calculated value of the Kruskal-Wallis test is less than the critical chi-square value, then we fail to reject the null hypothesis. This suggests there is insufficient statistical evidence to conclude that natural disasters create significantly different effects across sector returns.

5.4.2. Auto Regressive Distributed Lag (ARDL) approaches

The second set of models is to examine sentiment-return relations that is determined according to autoregressive process of equation (3) framework.

$$R^I_{i,t} = f(R^I_{i,t}, DSI_t, MMI_t, VIX_t) \tag{5.3}$$

Where, $R^I_{i,t}$ denotes the respective sectoral stock index return, DSI_t represent the disaster sentiment index, MMI denotes market mood index, and VIX is the market fear index or the volatility index.

The autoregressive framework depicted in equation (3) can be expressed as a linear multiple regression model, as represented by equation (4).

$$R^I_{i,t} = \alpha_0 + \beta_1 DSI_t + \beta_2 MMI_t + \beta_3 VIX_t + \varepsilon \tag{5.4}$$

Where, α_0 is the intercept or the constant term, $\beta_1, \beta_2, \beta_3$ are the estimated coefficient equation and ε denotes the epsilon, commonly referred to as the error term or the disturbance term. In line with the identified hypotheses, the investor sentiment and the sectoral stock index return relations was examined the cointegration, short-run dynamics, long-run bound test and stability of relationships.

Consequently, this study employs the unrestricted autoregressive distributed lag (ARDL) model, as developed and advanced by Pesaran and Shin (1998) and Pesaran et al. (2001) is employed to ascertain the nature of the long-run and short-run relationships between the sentiment variables and the sectoral index returns. The ARDL approach offers several econometric advantages over the Engle-Granger (1987) and the maximum likelihood-based (Johansen & Juselius, 1990; Johansen, 1991) cointegration techniques. Firstly, the bounds test does not necessitate pre-testing the variables to determine their order of integration, as the test can be conducted irrespective of whether the series are purely I (1), purely I (0), but not with I (2) (Pesaran et al., 2001). Secondly, the ARDL framework exhibits superior efficiency when dealing with small and finite sample sizes. Thirdly, the application of the ARDL methodology enables the obtainment of unbiased estimates of the long-run model and short-run in single equation approaches (Harris & Sollis, 2003; Pesaran et al., 2001). The estimated form of ARDL model is as follows.

$$\Delta R_{i,t}^{I} = \alpha_0 + \sum_{i=1}^{n} \beta_1 \Delta R_{i,t-p}^{I} + \sum_{i=1}^{n} \beta_1 \Delta DSI_{t-q} + \sum_{i=1}^{n} \beta_1 \Delta MMI_{t-q} + \sum_{i=1}^{n} \beta_1 \Delta VIX_{t-q} + \gamma_1 R_{i,t-1}^{I} + \gamma_2 DSI_{t-1} + \gamma_3 MMI_{t-1} + \gamma_4 VIX_{t-1} + \varepsilon_t \tag{5.5}$$

Where, Δ is the first difference of the variables, $\Delta R_{i,t}^{I}$ is the dependent variable or the sectoral index return, $R_{i,t-1}^{I}$, DSI_t, MMI_t, VIX_t are the independent variables or explanatory variables, and ε_t denotes a random error term. The autoregressive component is represented by $R_{i,t-p}^{I}$ and the lag value determining the extent of this self-referencing behavior. The lag of explanatory variables $DSI_{t-q}, MMI_{t-q}, VIX_{t-q}$ represent the distributed lag component in the model. The optimal lag lengths (p, q) are determined using Akaike Information Criterion (AIC) criteria.

Initially, the evidence of cointegrating relationship amongst the variables are examined. The main objective is to identify there is a significant existence of long run cointegration among the variables. This is accomplished by imposing restrictions on the estimated long-run coefficients of the independent variables for all the 18 sectoral indices using ARDL bound test and Wald-test. The F- statistics (Wald-test) computed on the joint null hypothesis is used to determine the cointegration significance at the standard conventional level. The null hypothesis of no cointegration (no long-run relationship) among the variables are jointly equal to zero (H_0=$\beta_1 = \beta_2 = \beta_3 = 0$) against the alternative jointly difference from zero ($H_0 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$) implies existence of long-run relationships.

After establishing the presence of a long-run cointegrating relationship among the variables, the ARDL framework can be readily employed to quantify the magnitude and nature of the long-run parameters. The long run effects are extracted from the unrestricted error correction model (ECM) on the above model (5). The estimated long-run coefficient is inspected as: $\Delta R_t = 0, \Delta R_{t-1} = 0,$ $\Delta DSI_t = 0, \Delta MMI_t = 0, \Delta VIX_t = 0$.

To examine the short-run dynamics, the error correction mechanism (ECM) version of the modified ARDL model will be employed. The error-correction term, which is the residual series obtained from the long-run cointegration regression equation estimated via OLS method. A statistically significant negative coefficient associated with the error-correction term provides evidence of short-run adjustment mechanisms.

$$\Delta R_{i,t}^{I} = \alpha_0 + \sum_{i=1}^{p_1} \gamma_1 R_{i,t-1}^{I} + \sum_{i=1}^{q_1} \gamma_2 DSI_{t-1} + \sum_{i=1}^{q_2} \gamma_3 MMI_{t-1} + \sum_{i=1}^{q_3} \gamma_4 VIX_{t-1} + + + \gamma_5 ECT_{t-1} + \varepsilon_t \tag{5.6}$$

Lastly, the stability of the sentiment-return relationship is analyzed using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squared recursive residuals (CUSUMSQ) method, which was originally introduced by Brown et al. (1975). The CUSUM test is designed to detect systematic changes in the regression coefficients, while the CUSUMSQ test aims to identify sudden departures from the consistency of the regression coefficients (Yin & Hamori, 2011; Tuyor et al., 2016). The equations used for estimating the CUSUM and CUSUMSQ statistics are as follows:

$$W_r = \sum_{t-1}^{r} W_t \tag{5.7}$$

$$S_r = \frac{\sum_{t-1}^{r} W_t^2}{\sum_{t-1}^{n} W_t^2} \tag{5.8}$$

5.4.3 Causality Test

Granger causality test, a statistical technique proposed by Clive Granger (1969) to examine potential causal relationships between time series variables. The underlying premise of Granger causality is that if a variable X_t "Granger-causes" another variable Y_t then

$$\mathbb{C}_{yt}(k|(y,x)_{t-1}) = \mathbb{C}_{yt}(k|y_{t-1}) \ \forall \ k \ \in \mathbb{R} \tag{5.9}$$

Where, $\mathbb{C}_{yt}\ (.|\mathcal{F})$ is the conditional distribution of y_t, then past values of X_t should contain not provide any additional information that improves the prediction of future values of y_t, once the value of y_t itself have been account for X_t is not granger cause y_t. To simplify the process, Granger proposed using the conditional expectation instead. The Granger causality test can be written in terms of conditional expectations as follows:

$$\mathrm{E}(y_t|(y,x)_{t-1}) = \mathrm{E}(y_t|y_{t-1}) \tag{5.10}$$

Where, E_{yt} $(.|\mathcal{F})$ denotes the mean of $\mathbb{C}_{yt}$ $(.|\mathcal{F})$, if equation (7) hold we can say that it the past values of X_t contain additional information that helps improve the prediction of y_t, beyond what is already contained in the past values of y_t alone. In other words, X_t Granger-causes y_t. To implement the Granger causality test, we estimate a vector autoregressive (VAR) model in its reduced form.

$$R_{i,t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{i,t-1} + \sum_{i=1}^{q} \beta_j Sentiment\ index_{,t-1} + \varepsilon_t \tag{5.11}$$

$$Sentimen\ index_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{i,t-1} + \sum_{i=1}^{q} \beta_j Sentiment\ index_{,t-1} + \varepsilon_t \tag{5.12}$$

Where, $R_{i,t}$ is the return of the sectoral index at time (t), $Sentimen\ index_t$ is the investor sentiment proxies for DSI, MMI and VIX respectively. The appropriate leg length for the causality test is determined using p and q and ε_t is the error term. The null hypothesis ($H_0 = \alpha_i = \beta_j = 0$), If the null hypothesis is rejected ($H_0 \neq \alpha_i \neq \beta_j \neq 0$) it implies stock return Granger cause sentiment index.

5.5. Result and Discussion

5.5.1 Impact of natural disaster on sectoral return

The Table 5.6 represents the impact of natural disasters on the BSE sectoral indices and overall market returns. The result for the market return exhibits a positive significant return in Energy (0.112) and Teck (0.043) at the 5 percent level. Further we also found a negative (-0.172) market reaction in metal index return. Moreover, sectors such as FMCG, Consumer Durables, Information Technology (IT), Oil and Gas, and Reality show negative returns during events and are not necessarily significant.

Taking a closer look at the market response toward specific natural disasters in the sectoral index, we found a significant positive impact on sectoral returns during avalanche calamities. Cold waves exhibited a significant increase in returns for the following sectors: commodities (0.20), energy (0.23), financial services industry

(0.10), metal (0.24), telecommunications (0.15), utilities (0.14), power (0.32), and TECK (0.15), and the overall market index also showed a significant positive effect. Cyclone exhibits a significant negative impact on information technology (-0.41), metal (-0.55), and positive (0.07) impacts on the overall market index. Earthquakes have a significant negative impact on consumer Durables, Energy, Healthcare, information technology, metal, telecommunication, and utilities sectors, and the overall market shows a lower expected return during earthquake events. Floods provide no significant market response; however, the period tends to show lower excess returns during this event. Glacier outbursts show a positive and negative impact on almost all sectors except Capital Goods. The coefficient on heatwaves provides a significant positive return on the energy (0.20), healthcare (0.06), power (0.59), telecommunication (0.13), and utilities (0.18) sectors. Storm has a significant negative impact on the industrial sector (-0.19), power (-0.28), and realties (-0.45). Finally, Landslide provides a positive coefficient for consumer durables (0.57), FMCG (0.37), information technology (0.32), and Teck (0.08), and a negative impact on the energy (0.51) sectors. Overall, it can be observed that there was a significant disaster effect on the Indian stock market and its sectoral index. The analysis highlights the varying impacts of different natural disasters on various market sectors, with some events leading to positive returns and others leading to negative returns across industries.

5.5.2 Estimate the effect of Natural disaster using K-W test

Furthermore, the study has estimated the rank-based non-parametric test following the same to check the robustness of the findings of the OLS model. As the return distributions of the sectoral return series show non-normality, there might be a possibility of spurious outcome. Estimates of the K-W test presented in Table 5.7 show the qualitative similarity of the findings like in the OLS model. Avalanches disaster have a significant impact at the 10% level on certain sector Auto, Bankex, Commodities, Consumer Discrepancies, Financial services, Metal, Oil & Gas, Power, and market index. Cold waves exhibit significant impact at the 5% level on the TECK sector and at the 1% level on the Power sector. Cyclones show a significant impact at the 5% level on the Information Technology sector and at the 1% level on the Commodities and Metal sectors. Floods provide a significant impact at the 5% level on the FMCG sector and at the 1% level on the Realty sector. Glacier outbursts exhibit a significant impact at the 5% level on the Consumer Discrepancies sector. Heat waves have a significant impact at the 10% level on the Power sector and at the 5% level on the Utilities sector. Storms have a significant impact at the 5% level on the Power and Utilities sectors, and at the 1% level on the Realty sector. Landslides have a significant impact (at the 10% level) on the FMCG and Healthcare sectors, (at the 5% level) on the Capital Goods, Commodities, Consumer Discrepancies, Consumer Durables, Energy, Industrial, Metal, and Oil & Gas sectors, and (at the 1% level) on the Market Index.

5.5.3 Extreme trading days

Furthermore, the study observed the rates of return during the 15 highest-gaining and 15 lowest-performing trading days for the market index, shedding light on the effects of exceptionally positive and negative return days. These observations guarantee temporal association between trading behaviour and natural events. Table 5.8 reveals that out of the 60 natural disaster events considered in the study period, only seven events were associated with extreme positive or negative returns. This finding suggests that extreme trading activity is not solely attributable to natural events. The result suggests that significant changes in the sectoral market during the study period were not primarily driven by factors other than natural disasters neither entirely rule out the possibility of a significant natural disaster effect on the Indian securities market.

Table 5.6: Impact of natural disaster on the sectoral and market index

	C	Natural Disaster	Avalanches	Cold wave	Cyclone	Earthquake	Flood	Glacier Outburst	Heat wave	Storm	Landslide
Auto	0.05 (1.37)	0.03 (1.05)	1.05* (31.74)	0.02 (0.15)	-0.03 (-0.21)	-0.60 (-1.28)	0.02 (0.21)	0.29* (8.74)	0.02 (0.20)	0.02 (0.18)	0.49 (1.53)
Bankex	0.06*** (1.73)	0.01 (0.15)	1.10* (30.31)	0.04 (0.69)	-0.14 (-0.60)	-0.59 (-0.86)	-0.01 (-0.07)	0.20* (5.52)	0.08 (0.78)	-0.09 (-0.75)	0.51 (1.25)
Capital Goods	0.06 (1.46)	0.05 (0.17)	0.53 (13.63)	0.22 (1.91)	-0.08 (-0.38)	-1.22 (-1.81)	0.00 (0.02)	0.06 (1.59)	-0.02 (-0.13)	-0.18 (-1.81)	0.59 (1.80)
Commodities	0.06*** (1.80)	0.13 (1.48)	1.13* (32.61)	0.20** (2.49)	-0.31 (-1.76)	-0.80 (-1.74)	0.03 (0.36)	0.56** (16.00)	0.01 (0.05)	-0.11 (-1.11)	0.43 (1.59)
Consumer discrepancies	0.06* (2.24)	0.01 (0.61)	0.85* (34.39)	0.08 (0.97)	-0.01 (-0.07)	-0.66 (-1.49)	-0.03 (-0.42)	0.45* (18.34)	0.11 (1.23)	-0.06 (-0.70)	0.23 (1.28)
Consumer Durables	0.06** (1.97)	-0.01 (-0.37)	0.98* (32.10)	0.29** (2.24)	-0.04 (-0.25)	-1.11** (-2.35)	0.04 (0.00)	0.51* (16.51)	0.10 (0.55)	-0.13 (-0.93)	0.57** (2.64)
Energy	0.04 (1.15)	0.11** (1.99)	0.39* (12.05)	0.23* (4.03)	0.17 (0.76)	-0.97* (-3.70)	0.06 (0.78)	0.81* (24.88)	0.20** (1.84)	0.03 (0.16)	-0.51* (2.83)
Financial Services	0.06*** (1.69)	0.02 (0.23)	1.31* (37.64)	0.10** (2.37)	-0.18 (-0.84)	-0.70 (-1.48)	0.00 (0.05)	0.31* (8.97)	0.07 (0.75)	-0.09 (-0.87)	0.48 (1.28)
FMCG	0.06* (2.80)	-0.07 (0.67)	0.17* (7.91)	-0.15 (-0.81)	-0.13 (-0.99)	-0.58 (-1.00)	-0.03 (-0.43)	-0.48* (-22.84)	0.09 (1.08)	-0.06 (-0.47)	0.37** (2.11)
Healthcare	0.06** (2.34)	0.01 (0.14)	0.18* (7.33)	0.04 (0.20)	-0.20 (-1.32)	-0.24* (-8.16)	0.06 (1.00)	-0.08* (-3.47)	0.06** (1.95)	-0.09 (-1.28)	0.11 (0.43)
Industrial	0.07*** (1.85)	0.04 (0.16)	0.72* (19.42)	0.21* (2.78)	-0.18 (-0.97)	-1.01** (-1.66)	0.02 (0.21)	0.36* (9.74)	0.00 (0.00)	-0.19** (-1.97)	0.46 (1.35)
Information Technology	0.05*** (1.87)	-0.02 (0.66)	0.08* (2.66)	0.18 (1.36)	-0.41** (-1.89)	-0.12* (-0.79)	0.02 (0.30)	0.34* (11.47)	-0.07 (-0.40)	0.06 (0.41)	0.32** (2.15)
Metal	0.03 (0.70)	-0.17** (2.01)	1.41* (32.53)	0.24* (2.84)	-0.55** (-1.88)	-1.04*** (-2.84)	0.07 (0.66)	0.32* (7.31)	0.02 (0.13)	-0.07 (-0.49)	0.75** (2.18)
Oil & Gas	0.03 (0.87)	-0.01 (-0.37)	1.16* (37.40)	0.22* (3.47)	0.22 (0.96)	-0.88* (-3.41)	0.03 (0.38)	0.23* (7.33)	0.23 (1.30)	-0.07 (-0.60)	0.39 (1.56)

Power	0.03 (1.05)	0.08 (1.02)	0.88* (26.62)	0.32* (5.93)	0.03 (0.09)	-1.09 (-1.39)	0.02 (0.21)	0.16* (4.71)	0.59** (2.00)	-0.28** (-2.48)	0.33 (1.15)
Realty	0.07 (1.37)	-0.13 (-1.17)	0.46* (9.25)	0.19 (0.69)	-0.24 (-1.27)	-1.03 (-1.49)	-0.11 (-0.81)	0.51* (10.16)	-0.09 (-0.68)	-0.45** (-2.46)	0.30 (0.57)
Teck	0.05** (4.94)	0.04** (2.13)	0.07* (7.37)	0.15* (10.98)	0.05 (1.43)	0.07 (1.22)	0.01 (0.54)	-0.06* (-7.05)	0.01 (0.19)	-0.03 (-0.68)	0.08** (2.55)
Telecommunication	0.03 (1.21)	0.01 (0.14)	0.09* (4.38)	0.15*** (1.62)	0.01 (0.09)	-0.48*** (-1.79)	-0.03 (-0.51)	-0.13* (-6.35)	0.13* (2.89)	0.04 (0.51)	0.04 (0.61)
Utilities	0.03* (4.48)	0.02 (0.91)	-0.06* (-7.46)	0.14* (3.90)	0.04 (0.78)	-0.18* (-8.47)	-0.01 (-0.40)	-0.06* (-8.53)	0.18* (2.52)	0.11 (1.51)	0.03 (1.18)
Market index	0.06 (0.62)	0.01 (0.18)	0.07 (1.59)	0.07*** (1.68)	0.06* (2.19)	0.10 (1.49)	0.001 (0.92)	-0.04* (-3.81)	0.03 (0.78)	-0.05 (-1.54)	0.03 (0.93)

Source*: Author's Computation using Stata*

Note(s): The table presents the estimates from an Ordinary Least Squares (OLS) regression model with the Newey-West heteroscedasticity and autocorrelation-consistent (HAC) standard errors. The Newey-West estimator is used to account for potential heteroscedasticity and serial correlation in the error terms. The t-statistics are depicted in parenthesis. *, **, *** denotes significance at the 1 %, 5%, and 10% level respectively.

Table 5.7: Impact of natural disaster on the sectoral and market index using K-W test

	Avalanches	Cold wave	Cyclone	Earthquake	Flood	Glacier Outburst	Heat wave	Storm	Landslide
Auto	2.70***	0.355	1.633	1.168	0.451	0.50	0.187	0.188	0.001
Bankex	2.578**	0.008	0.380	0.432	0.397	0.190	0.181	0.027	1.745
Capital Goods	1.068	1.945	0.062	2.596***	1.793	0.035	0.007	0.909	4.765**
Commodities	2.594***	0.847	2.128***	2.167***	0.002	1.179**	0.001	0.571	3.496**
Consumer discrepancies	2.615***	0.002	0.044	1.739	1.255	1.356**	0.771	0.129	2.809***
Consumer Durables	2.469	0.908	0.003	3.750**	0.088	1.137	0.691	0.764	5.924**
Energy	0.744	0.897	0.729	4.251**	0.023	2.093	1.022	0.013	6.642**
Financial Services	2.744***	0.162	0.704	1.678	0.119	0.615	0.102	0.172	2.011
FMCG	0.337	0.011	0.680	0.387	3.617**	0.110	0.389	0.436	5.556*
Healthcare	0.279	0.024	1.611	1.146	1.660	0.740	0.123	0.627	2.183***
Industrial	1.696	1.236	0.832	2.167***	0.317	0.722	0.024	1.178	3.571**
Information Technology	0.013	0.349	4.406**	0.261	0.237	0.656	0.156	1.010	1.693
Metal	2.428***	1.127	2.887***	3.147**	0.064	0.258	0.000	0.152	5.268*
Oil & Gas	2.701**	0.842	0.680	3.876**	0.002	0.252	2.283**	0.365	2.599**
Power	2.228***	2.062***	0.577	1.503	1.260	0.152	4.757*	2.640**	2.861**
Realty	0.711	0.082	1.013	1.549	2.463***	0.767	0.189	3.921**	0.942
TECK	0.019	5.143**	1.244	0.492	0.008	0.269	0.016	0.744	1.496
Telecommunication	0.282	0.673	0.101	2.201***	0.037	0.599	2.566***	0.590	0.095
Utilities	0.065	1.552	0.093	2.181***	0.577	0.103	4.545**	2.649***	0.318
Market index	2.459**	0.004	0.701	1.311***	0.234	1.229	1.256	1.042	5.633*

***Source**: Author's Computation using Stata*

Note(s): The estimate output of K-W test and its interpretation, and highlight the significance levels used to assess the impact of natural disasters on different sectors. *, **, *** denotes significance at the 1 %, 5%, and 10% level respectively. A higher test statistic value indicates a greater difference in medians among the groups, suggesting a significant impact of the natural disaster on that particular sector.

Table 5.8: Rates of return on the extreme trading days on the market return

Date	Negative Return	Positive Return	Possible Explanation	Event Day?
31-May-13	-2.28%		The heat wave impacts the on-mainland India RBI's poor inflation outlook and GDP falling	Yes
28-Jun-13		2.72%	2013 Taper Tantrum	No
16-Aug-13	-4.05%		Indian own financial crisis	No
18-Oct-13		2.26%	RBI governor took steps to stabilize the rupee	No
09-May-14		2.87%	Modi effect	No
04-Sep-15	-2.21%		Worst hit Flood across India US Fed rate hike worries	Yes
22-Jan-16		1.96%		No
24-Jun-16	-2.26%		UK "Earthquake" Crush Global market	Yes
11-Nov-16	-2.57%		Heavy rain and flood	Yes
02-Feb-18	-2.37%		Global economic weakness and Increase NPA	No
05-Oct-18	-2.28%		RBI policy outcome	No
12-Oct-18		2.13%	Cyclone Tilti Market volatile in favour of rebound	Yes
21-Dec-18	-1.91%		Post Federal reserve rate Hike	No
20-Sep-19		5.19%	FM announced reduction in corporation tax	No
01-Feb-20	-2.46%		Corona Stings D-Street	No
28-Feb-20	-3.71%			
06-Mar-20	-2.35%			No
13-Mar-20		3.96%		No
03-Apr-20	-2.41%			No
20-Mar-20		5.59%		Mo
09-Apr-20		4.15%		No
17-Apr-20		3.17%		No
30-Apr-20		3.00%		No
26-Feb-21	-3.87%		Covid- 19 Second wave	No
30-Apr-21	-2.00%			No
21-May-21		1.95%	Cyclone Tukatae	Yes
25-Sep-21		2.26%	NDMA inform about Cyclone over the next days	Yes
26-Nov-21	-2.91%		Covid variant sparks sell-off as covid-19 cases reduced worldwide	No
25-Feb-22		2.41%	Market rebounded despised Russian Ukraine war	No
20-May-22		2.86%	China's central bank cut its five-year loan prime rate	No

***Source**: Author's Computation using Stata*

Note(s): To ensure that the natural disaster events do not influence the results, the tests were repeated without considering data points related to natural disasters. These tests were specifically conducted to analyse the rates of return on the 15 best and 15 worst trading days for the market index, highlighting the impact of extreme positive and negative return days.

5.6. Relationship of investors sentiment and sectoral stock return

5.6.1 Wald test and Bound test

The descriptive statistics in Table 5.2 and Table 5.4 show a significant requirement for the use of ARDL. The results indicate that the order of integration and serial integration are satisfied for all models. The variables inspected using ARDL and

KPSS show all the variables are stationary at fist difference at 5 percent level for all the model and none of the variable are of I (2). When the normality test indicates significance for all variables, it suggests that the data does not follow a normal distribution. However, according to the central limit theorem, this violation of normality can be disregarded in cases involving large sample sizes (Ghasemi & Zahediasl, 2012; Kwak & Kim, 2017).

Table 5.9 shows the cointegration analysis of Wald test and Perasan bound test upper and lower-level tabulated values. To ensure that the serial correlation problem exists in the model, the test opts for performing the ARDL bound test with no intercept and no trend. The results presented in the Table 5.9 indicate the bound F-statistic exceeds the upper bound critical value, leading to a straightforward rejection of the null hypothesis of no cointegration among the variables under consideration. The Wald test provides additional support for the presence of cointegration among the variables under investigation. This finding indicates that we can move forward to explore both the long-run and short-run dynamics through the Autoregressive Distributed Lag (ARDL) model and examine the error correction mechanism. The error correction mechanism captures the speed at which the dependent variable adjusts towards its long-run equilibrium after a short-run shock, thereby ensuring that deviations from the long-run relationship are temporary and convergence ultimately occurs.

Table 5.9: Bound and Wald test result with Bound test critical value

	Bound test	**Wald Test**	**P-Value**
Auto	74.5340	4.7333	0.00
Bankex	14.1316	3.3013	0.01
Capital Goods	69.9948	6.2430	0.00
Commodities	35.3404	4.5813	0.00
Consumer discrepancies	65.8461	6.8767	0.00
Consumer Durables	61.3545	3.3428	0.01
Energy	95.3687	2.9157	0.02
Financial Services	14.8221	4.4461	0.00
FMCG	69.0625	1.9799	0.03
Healthcare	7.66452	2.4744	0.03
Industrial	62.6495	5.6870	0.00
Information Technology	68.1525	5.6870	0.00
Metal	37.6700	3.6881	0.00
Oil & Gas	92.3380	2.7032	0.03
Power	76.4873	5.1023	0.00
Realty	38.9647	26.0354	0.00
TECK	37.3762	6.2285	0.00
Telecommunication	29.2323	20.6728	0.00

Utilities	68.3510	4.6672	0.00
Bound test Critical Value			
	Critical Value	Lower Bound	Upper Bound
Asymptotic: n=1000	10%	2.37	3.2
	5%	2.79	3.67
	2.5%	3.15	4.08
	1%	3.65	4.66

Source*: Author's Computation using EViews*

5.6.2. Long run Relationship

The analysis investigates the long-term association between sentiment and returns presented in Table 5.10. The presentation solely focuses on reporting the coefficient estimates, their corresponding p-values, and t-statistics. This selective reporting approach is driven by the primary objective of identifying the numerical values of the parameters and assessing the statistical significance of their associated p-values. The findings indicate that the disaster sentiment proxy exhibits a significant influence on various sectors, including Capital Goods, Energy, FMCG, Financial Services, Industrial, and Power sectors. This result is quite intriguing as it suggests that these sectors are more or less susceptible to the impacts of natural disaster calamities. For instance, If the disaster sentiment increases by 1.0 percent, output in Auto sector return will increased by 0.039 percent and it will decrease by 0.13 percent in Bankex Sector. The empirical analysis reveals that the MMI sentiment proxy exerts a highly statistically significant influence at the 0.01 percent and 0.05 percent significance levels across most sectors, with the exception of Consumer Durables, Industrial, and Realty sectors. Conversely, the fear index or VIX proxy exhibits a significant positive impact on expected returns in the industrial and realty sectors. However, an increase in the fear index leads to a decrease in expected returns for sectors such as FMCG, Healthcare, Metals, Power, IT, and Telecommunications. The diagnostic test results presented in Table 9 indicate that the underlying assumptions of normality, homoscedasticity (homogeneity of variance), and absence of serial correlation are satisfied. Additionally, the condition of the Durbin-Watson (DW) statistic exceeding the R-squared value is met, further reinforcing the validity of the model. These findings suggest that the MMI sentiment proxy serves as a reliable indicator of market sentiment, capturing the overall investor sentiment and its implications for various sectors. Nonetheless, it is prudent to consider alternative proxies like disaster sentiment that may potentially capture the nuances of market sentiment within a specific span of time especially during the uncertain events. The result support the validity of impact of disaster sentiment in the stock return.

5.6.3. Short Run Relationship

The short-run dynamics among the variables under consideration are empirically examined, and the results are presented in Table 5.11. For instance, the incorporation of autoregressive distributed lag (ARDL) models with vector error correction models (VECMs) could provide valuable insights into the short-run dynamics, particularly in the presence of potential endogeneity or feedback effects among the variables. The empirical findings reveal that the disaster sentiment proxy exerts a more pronounced impact in the short run compared to its long-run counterpart. A significant negative relationship is observed between the disaster sentiment index (DSI) and sectoral returns across various industries, including the Auto, Capital Goods, FMCG, Financial Services, Industrial, Power, Metals, Oil and Gas, and Realty sectors. A positive relationship was found in information technology sector. These results shed light on the short-term dynamics and the heightened sensitivity of sectoral returns to disaster-related sentiments. For instance, If DSI sentiment increase by one percent it will bring down the price of auto sector by 0.014 percent and if the variable moves away from the long run equilibrium by 1 percent, the system will readjust with a speed of -0.96 percent as suggested by error correction mechanism. The same is applicable in another variables. The MMI sentiment proxy exhibit a highly statistically significant influence at the 0.01 percent and 0.05 percent significance levels. A positive relation was found in Auto, Bankex, Capital goods, Commodities, Consumer discrepancies, Consumer durables, Energy, Financial services, Healthcare, Industrial, Information technology, Metal, Power, Telecommunication, and Realty. A negative significant relationship was found in FMCG, Teck, and Utilities. Conversely, the fear index or VIX proxy exhibits a significant positive relationship on Healthcare, Teck, Telecommunication, Utilities sector and negative relationship was found various sectors like Auto, Capital Goods, FMCG, Metal, Power, and Realty.

Table.5.10: Summary of Long-run ARDL test for cointegration regression

Sectoral	Optimum Lag	Coefficients				
		C	**R_{t-1}**	**DSI**	**MMI**	**VIX**
Auto	(1,0,0,0)	0.037 (1.287)	0.039** (0.763)	-0.014 (-0.523)	*4.489** (3.569)	-0.047 (-1.254)
Bankex	8,0,0,0)	0.073** (0.039)	-0.129** (0.041)	-0.022 (0.472)	*3.915** (0.009)	-0.061 (0.167)
Capital Goods	1,1,0,0	0.036 (0.987)	0.090 (1.415)	-0.046** (-1.735)	*6.065** (4.974)	-0.071 (-1.425)
Commodities	2,0,0,1	0.034 (1.095)	0.097** (1.755)	-0.015 (-0.534)	*5.584** (4.857)	0.063 (1.640)
Consumer discrepancies	(1,0,0,0)	0.047 (1.830)	0.112 (1.810)	0.000 (0.018)	*3.953** (4.290)	-0.048 (-1.446)
Consumer Durables	(1,0,1,0)	0.043 (1.350)	0.092 (1.637)	-0.007 (-0.279)	-1.753 (-1.257)	0.030 (0.768)
Energy	(1,0,0,0	0.059** (1.917)	-0.113** (-2.142)	-0.044** (-1.994)	2.470** (2.449)	-0.027 (-0.653)
Financial Services	(8,0,0,0)	0.063** (1.941)	-0.142** (-2.454)	-0.020 (-0.827)	*4.388** (3.390)	-0.053 (-1.341)
FMCG	(1,0,5,0)	0.046 (1.987)	0.033 (0.696)	-0.041*** (-1.794)	2.927** (2.513)	-0.058 (-1.717)
Healthcare	(11, 0, 1, 7)	0.047** (1.986)	0.093 (1.371)	-0.002 (-0.100)	1.958** (2.211)	-0.077** (-2.865)
Industrial	(1,2,1,1)	0.028 (0.871)	0.088 (1.395)	0.053** (2.009)	2.297 (1.552)	0.078*** (1.898)
Information Technology	1,3,0,0	0.035 (1.269)	0.016 (0.754)	*-0.084** (-2.771)	0.115 (0.096)	0.041 (1.031)
Metal	(2,5,0,0)	0.019 (0.489)	0.098*** (1.743)	-0.046 (-0.974)	*6.488** (4.653)	-0.081*** (-1.659)
Oil & Gas	(1,0,0,0)	0.042 (1.384)	-0.095 (-1.839)	-0.029 (-1.042)	2.661 (2.619)	-0.042 (-1.034)
Power	1,2,0,0	0.020 (5.776)	0.027 (4.590)	-0.043** (0.463)	*4.638** (5.129)	-0.089*** (-2.619)
TECK	4,0,4,3	0.034 (2.461)	*0.188** (-2.380)	0.003 (1.007)	*1.332** (4.605)	-0.029** (-4.088)
Telecommunication	4,0,0 3	0.048 (2.461)	-0.163** (-2.380)	0.022 (1.007)	*3.199** (4.605)	*-0.105** (-4.088)
Utilities	4,0,4,2	*0.045** (5.192)	*-0.185** (-3.470)	-0.002 (-0.301)	*1.350** (5.328)	0.023 (1.382)
Realty	1,2,1,1	0.005 (0.922)	0.054 (1.056)	0.087** (1.992)	3.378 (1.430)	0.200 (3.138)

***Source**: Author's Computation using EViews*
Note: *, **, *** denotes significance at the 1 %, 5%, and 10% level respectively

Table 5.11: Result of Diagnostic checking for cointegration regression

Sectoral	Diagnostics					
	Adj R^2	**DW stat**	**LM(2)**	**ARCH(2)**	**Q stat(1)**	**Q stat (5)**
Auto	0.039	2.003	0.082	1.297	0.001	1.583
Bankex	0.052	1.993	0.518	1.452	0.028	0.053
Capital Goods	0.066	1.990	1.839	2.051	0.002	5.526
Commodities	0.055	2.042	3.179	0.019	0.167	2.674
Consumer discrepancies	0.060	1.985	0.822	5.185	0.013	2.206
Consumer Durables	0.040	2.006	1.482	3.441	0.016	4.000
Energy	0.031	1.992	0.046	0.034	0.001	1.265
Financial Services	0.068	1.989	0.631	1.375	0.044	0.197
FMCG	0.054	1.996	0.020	0.077	0.000	2.678
Healthcare	0.020	2.000	0.725	0.174	0.654	5.948
Industrial	0.093	2.034	3.606	3.510	0.106	3.608
Information Technology	0.039	1.983	0.428	0.023	0.008	5.176
Metal	0.064	2.005	0.472	0.076	0.012	1.401
Oil & Gas	0.018	2.000	0.005	0.327	0.002	4.151
Power	0.063	1.985	1.322	4.886	0.013	4.701
TECK	0.490	2.124	14.586	11.733	2.698	7.209
Telecommunication	0.125	2.001	0.285	8.133	0.028	6.824
Utilities	0.412	1.985	1.048	4.061	0.005	3.694
Realty	0.074	2.003	0.856	0.821	0.020	2.724

***Source**: Author's Computation using EViews*

Note(s): Four diagnostic tests were conducted to assess the validity of the models, including serial correlation, functional form misspecification, non-normality, and heteroscedasticity. The null hypothesis in each of these tests assumed the absence of the respective diagnostic issue, while the alternative hypothesis indicated the presence of such problems. Consequently, the null hypothesis could not be rejected, implying that the models were free from any of the diagnostic concerns under consideration.

Table 5.11: Assessment of short run relationship

Sectoral	**Optimum Lag**	**Rt-1**	**DSI**	**MMI**	**VIX**	**C**	**ECT**
Auto	(1,0,0,0)	-0.961 (1.287)	-0.014** (-1.773)	4.489* (-0.523)	-0.047* (3.569)	0.037 (-1.254)	-0.96*
Bankex	(8,0,0,0)	-1.092 (-7.535)	-0.022 (-0.710)	3.915* (2.713)	-0.061 (-1.440)	0.041** (2.195)	-1.01*
Capital Goods	(1,1,0,0)	-0.910 (-17.992)	-0.097** (-1.992)	6.065* (4.066)	-0.071*** (-1.607)	0.036 (1.052)	-0.91*
Commodities	(2,0,0,1)	-0.968** (-1.985)	-0.015 (-0.521)	5.584* (4.244)	-0.043 (0.392)	0.034 (1.114)	-0.86*
Consumer discrepancies	(1,0,0,0)	-0.888* (-17.535)	0.001 (0.018)	3.953* (3.832)	-0.048 (-1.575)	0.047** (1.983)	-9.21*
Consumer Durables	(1,0,1,0)	-0.908 (-17.433)	-0.007 (-0.256)	3.851* (2.952)	0.030 (0.763)	0.043 (1.465)	-0.919
Energy	(1,0,0,0)	-1.113* (-21.463)	-0.044 (-1.456)	2.470*** (1.766)	-0.027 (-0.653)	0.059*** (1.819)	-1.113**
Financial Services	(8,0,0,0)	-0.991* (-7.386)	-0.020*** (-1.721)	4.388* (3.403)	-0.053 (-1.390)	0.063** (2.100)	-0.956**

FMCG	(1,0,5,0)	-0.967* (-18.443)	-0.080** (-1.955)	-3.465* (-2.582)	-0.058*** (-1.741)	0.046** (1.899)	-0.979**
Healthcare	(11, 0, 1, 7)	-0.885* (-4.567)	-0.002 (-0.092)	2.670* (2.784)	0.077** (2.565)	0.047*** (1.875)	-0.962**
Industrial	(1,2,1,1)	-0.912* (-17.557)	-0.053*** (-1.811)	6.865* (5.009)	-0.049 (-1.201)	0.028 (0.890)	-0.912
Information Technology	(1,3,0,0)	-0.984* (-18.439)	0.062* (3.178)	2.453* (2.679)	0.085 (2.898)	0.035 (1.262)	-1.079
Metal	(2,5,0,0)	-0.920* (-12.600)	-0.101* (3.275)	6.488* (3.887)	-0.081*** (-1.620)	0.019 (0.491)	-0.914
Oil & Gas	(1,0,0,0)	-1.095* (-21.209)	-0.029** (-0.961)	2.661 (1.922)	-0.042 (-1.026)	0.042 (1.325)	-1.094
Power	(1,2,0,0)	-0.973* (-19.145)	-0.046** (-1.629)	4.638* (3.535)	-0.089** (2.154)	-2.295 (1.692)	-0.973
TECK	(4,0,4,3)	-0.635* (-4.383)	-0.001 (-0.301)	-1.331* (-5.796)	0.029* (3.543)	0.068* (5.601)	-0.349**
Telecommunication	(4,0,0 3)	0.163* (3.305)	0.022 (1.076)	3.199* (3.378)	0.105* (3.873)	0.048** (2.191)	-1.181**
Utilities	(4,0,4,2)	-1.300* (-11.172)	-0.002 (-0.257)	-1.350* (-3.002)	0.023** (-2.236)	0.045* (4.564)	-1.300*
Realty	(1,2,1,1)	-0.946 (-8.284)	-0.087** (-1.958)	7.478 (3.575)	-0.114*** (-1.829)	0.005 (0.105)	-0.946

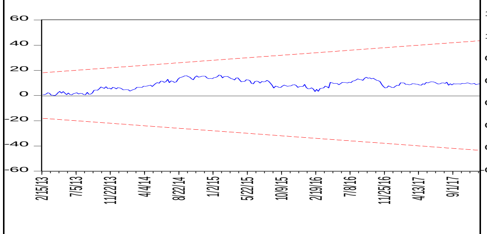
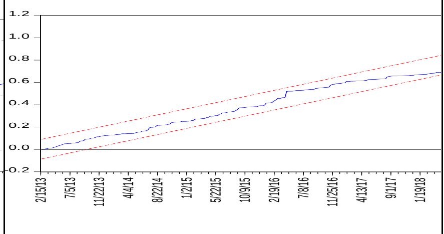
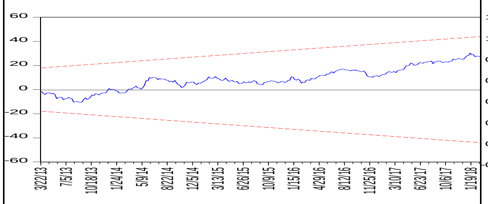
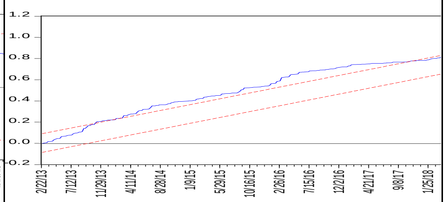
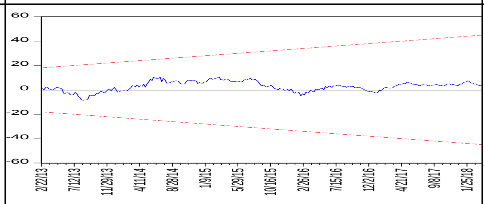
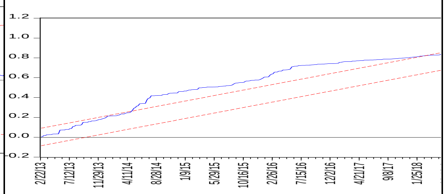
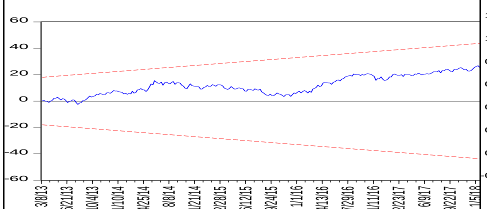
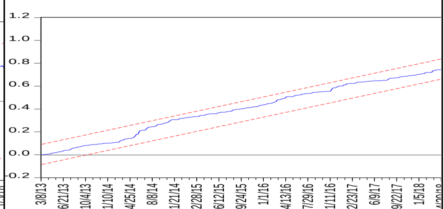
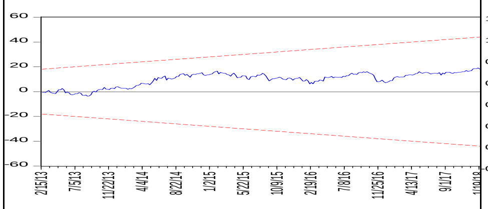
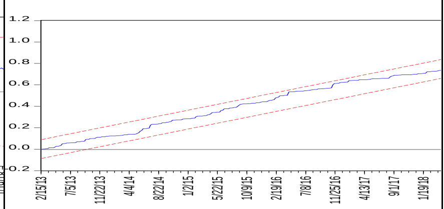
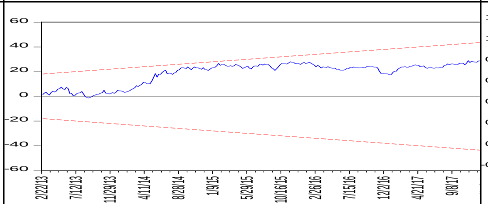
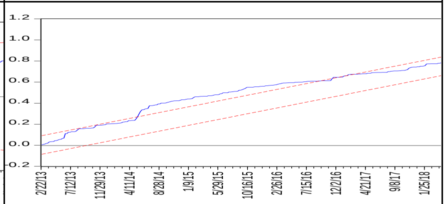
Source: *Author's Computation using EViews*
Note: *, **, *** denotes significance at the 1 %, 5%, and 10% level respectively

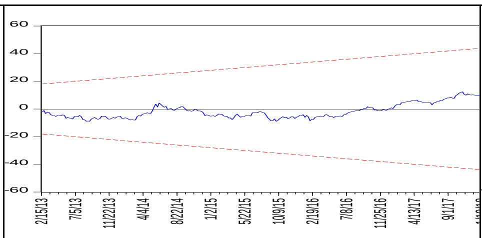
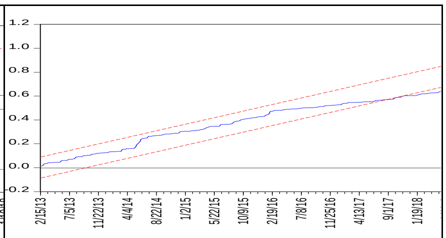
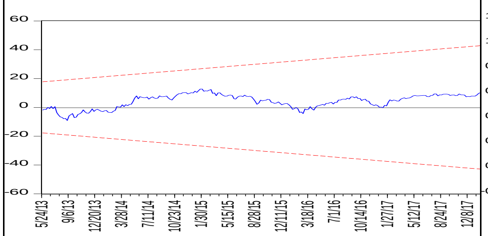
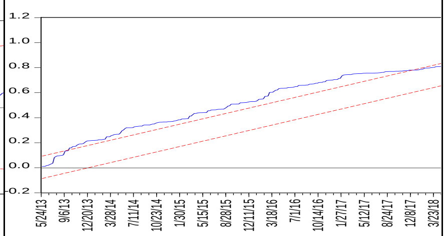
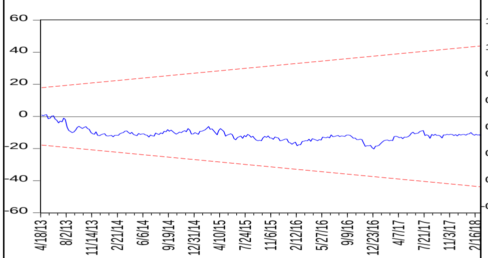
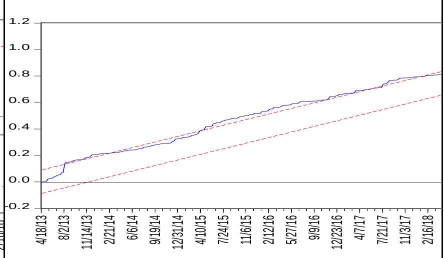
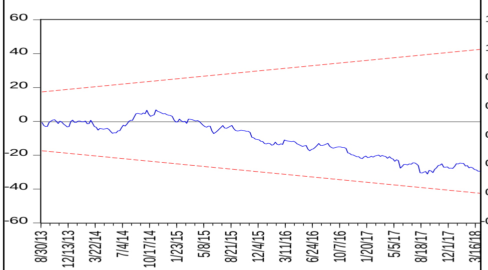
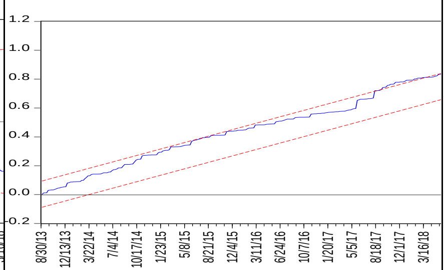
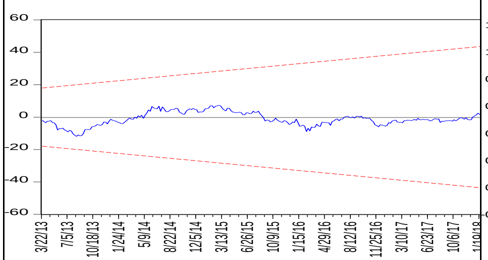
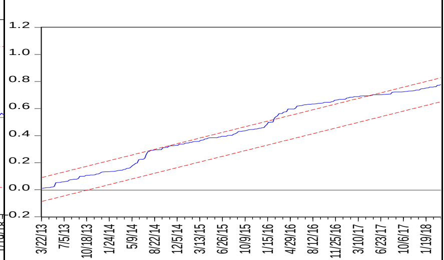
5.6.4 Stability test

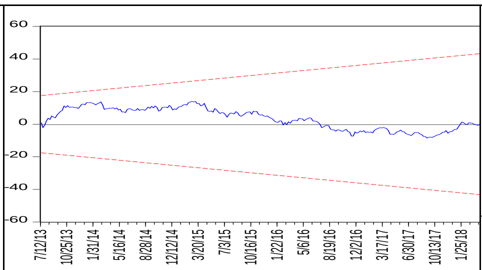
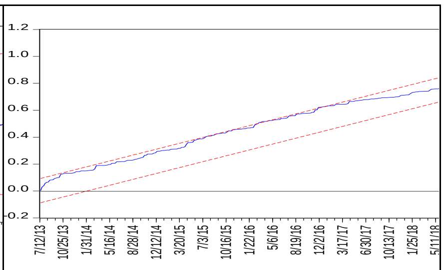
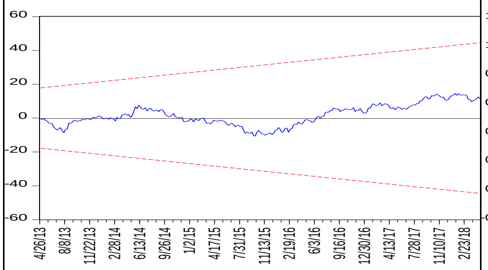
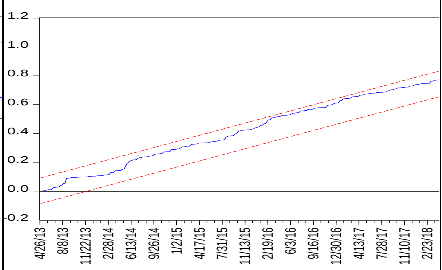
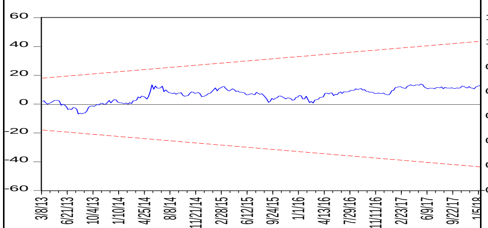
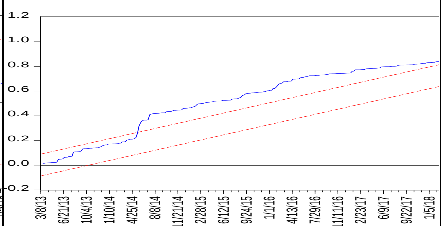
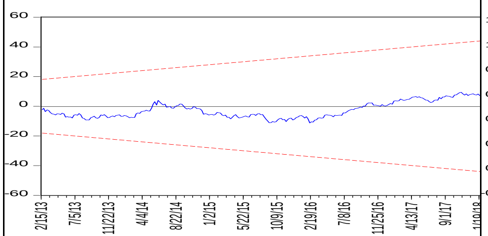
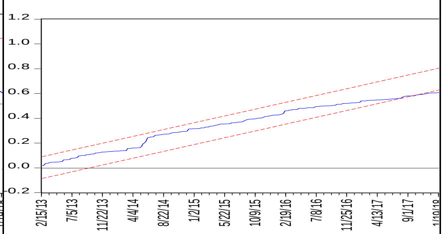
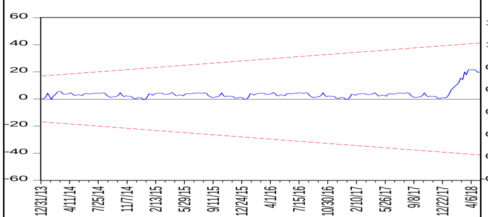
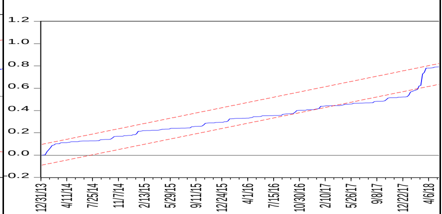
The stability of the relationship among the variables was analysed to assess whether the impact of sentiment remained consistent over time. For these two statistical tests, the cumulative sum (CUSUM) of the recursive residuals test and the cumulative sum of squares (CUSUMSQ) test were used, as proposed by Pesaran and Pesaran (1997). The cumulative sum test helps identify gradual and systematic shifts in the regression coefficients. On the other hand, the cumulative sum of squares test is used to detect abrupt departures from the constancy of the regression coefficients. The financial instability hypothesis suggests that if market sentiment, driven by investor emotions and psychology, becomes a dominant force, it can lead to market instability and volatility (Dow, 2011). This aligns with the notion that non-economic factors, such as human behaviour and cognitive biases, play a significant role in shaping economic outcomes (Akerlof & Shiller, 2009). Even though such instability and inefficiencies caused by sentiment may be short-lived, they are likely to persist in markets as long as individual, non-professional investors continue to participate in trading activities (Slezak, 2003). This is because ordinary investors are prone to being influenced by emotional factors, leading to the formation of financial fads, periods of excessive optimism (euphoria), and periods of excessive pessimism (gloom) in the markets (Sanford, 1994).

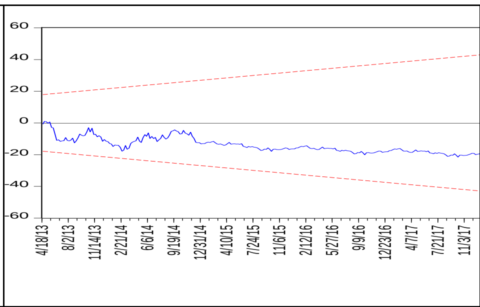
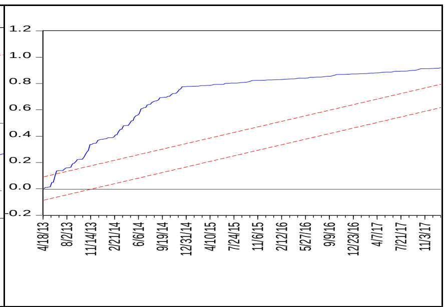
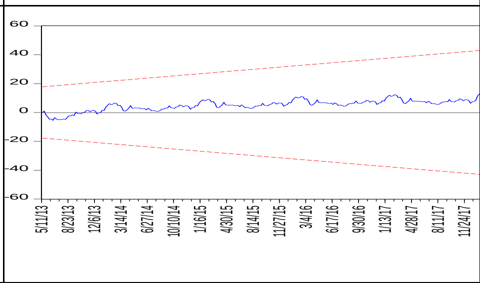
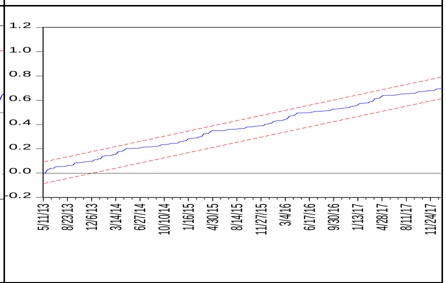
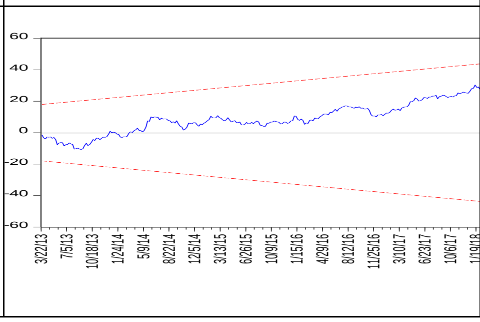
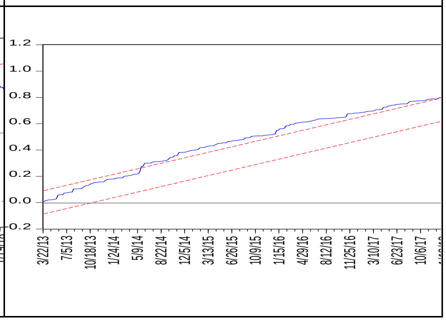
The CUSUM and CUSUMSQ test results, summarised in Figure 5.5, aim to examine the constancy of regression coefficients for all explanatory variables concerning stock market returns. The plots of the CUSUM statistics falling within the 5% critical bounds indicate an absence of instability in the coefficients, suggesting parameter stability (Ploberger & Krämer, 1992). These stability tests seem to indicate the sentiment proxies with three control variables are persistent in relation to stock market returns. However, the CUSUMSQ plot in certain sector like power, telecommunications, capital goods, banking, consumer durables, and financial services, the sentiment-returns relationship appears to bypass the critical bounds temporarily but revert toward the critical area, the model can still be considered stable (Bahmani-Oskooee & Ng, 2002). This phenomenon, known as "returning to stability," is commonly observed in economic time series data and does not necessarily invalidate the stability of the model (Giles & Godwin, 2012). This aligns with the literature on structural stability tests, which suggests that transitory exceedances of the critical bounds do not necessarily imply parameter instability, provided that the deviations are not sustained (Leybourne & Newbold, 2000). Thus, the result provides support to the persistency and heterogeneity role of sentiment in the Indian stock return. The results corroborate the notion that sentiment plays an enduring role in influencing stock price movements, and its effect manifests differently across various sectors and firm characteristics.

Figure 5.5: Summary of stability relationship test

Sectoral indices /Stability test	COSUM	COSUMSQ
Auto		
BankEx		
Capital Goods		
Commodities		
Consumers Dispensaries		
Consumer durables		

Energy		
Financial Services		
FMCG		
Healthcare		
Industrial		

Information Technology		
Metal		
Power		
Oil & Gas		
TecK		

Telecom		
Utilities		
Realty		

Source: Author's computation

5.6.5 Robustness test using Granger Causality test

Finally, the Granger causality test was performed to establish the causal relationship between disaster sentiment and other variables of interest particularly stock that are directly impacted by natural disaster. The results indicating a predictive ability of one variable for the other variable are presented in Table 5.12. For instance, we should not expect sector like consumer durables, commodities, metal etc. to cause an increase stock return or investor sentiment due to natural disaster. The finding reveals that Energy sector and Teck sector return leads disaster sentiment proxies. This implies a unidirectional causality running from stock returns to investor sentiment rather than the reverse. This result contrasts with the conventional wisdom and existing literature which posits that investor sentiment drives stock prices and returns (Baker & Wurgler, 2006, Da et al., 2015). However, the Disaster Sentiment Index (DSI) exhibits Granger causality in utmost sectors like capital goods, industrial, power, telecommunication realty, and the overall market index return. This implies that the DSI has predictive power over the future returns of these sectoral indices. The result confirmed the finding of (Deryugina et al., 2012; Feria-Domínguez et al., 2020; Halim & Zen, 2017; Krueger et al., 2021) that stock probe to disaster emergency handling have significant direct impact on abnormal return. Overall, the results highlight the importance of considering disaster-related sentiment and its potential impact on asset prices, particularly for sectors and firms more vulnerable to natural disasters and climate-related risks.

Table 5.13: Granger Causality test results

Lag length	Null hypothesis	F-statistic	P-value
1	Capital Goods does not Granger Cause DSI	0.27396	0.6015
	DSI does not Granger Cause Capital Goods	1.82286	0.0911
0	Bankex does not Granger Cause DSI	0.60393	0.4376
	DSI does not Granger Cause Bankex	0.64370	0.4229
1	Consumers Durables does not granger cause DSI	0.30975	0.5782
	DSI does not granger cause Consumers Durables	1.02362	0.3123
1	Energy does not granger cause DSI	2.08702	0.0794
	DSI does not granger cause Energy	0.91885	0.3384

4	Financial Services does not granger cause DSI	1.52700	0.1464
	DSI does not granger cause Financial Services	1.45736	0.1717
0	FMCG does not granger cause DSI	0.26282	0.769
	DSI does not granger cause FMCG	1.79429	0.1677
1	Health does not granger cause DSI	1.58646	0.2061
	DSI does not granger cause Health	0.27115	0.7627
2	Industrial does not granger cause DSI	0.45051	0.6377
	DSI does not granger cause Industrial	2.73805	0.066
3	Information Technology does not granger cause DSI	0.89312	0.4448
	DSI does not granger cause Information Technology	2.75719	0.0423
1	O & G does not granger cause DSI	0.32979	0.5661
	DSI does not granger cause O & G	0.14423	0.7043
2	Power does not granger cause DSI	0.98969	0.3727
	DSI does not granger cause Power	2.91162	0.0557
2	Realty does not granger cause DSI	0.05581	0.9457
	DSI does not granger cause Realty	2.96464	0.0528
4	Teck does not granger cause DSI	4.24698	0.0005
	DSI does not granger cause Teck	1.42440	0.1760
5	Telecommunication does not granger cause DSI	1.59183	0.1616
	DSI does not granger cause Telecommunication	1.85790	0.1010
9	Utilities does not granger cause DSI	1.04472	0.4038
	DSI does not granger cause Utilities	1.17825	0.3079
1	Sensex does not granger cause DSI	0.57434	0.5636
	DSI does not granger cause Sensex	2.30136	0.0916

Source: Author's computation

5.7 Chapter conclusion

The primary aim of this chapter is to investigate the effects of natural calamities and analyse how catastrophic events influence stock market performance, returns, and the potential co-movement and linkages between natural disaster sentiment and stock market returns. Natural calamities have a substantial influence on financial markets, which is widely acknowledged in the literature. Studies have shed light on the intricate connections between natural calamities and economic performance; however, the impact of extreme events, such as natural calamities, has not received the same level of attention in the Indian equity market. The study further extends in filling the gap advancing research in this area on how sentiment surrounding natural disasters impacts stock behaviour. The natural calamities period has not been examined in great detail in the literature in terms of examining investor sentiment in stock returns when investor's lives are imperilled. For this Disaster sentiment index has been developed to capture investor perception and belief during this extreme weather events. It endeavours to understand whether shifts in collective sentiment towards these calamitous occurrences exhibit any discernible patterns or relationships with equity market fluctuations.

The key conclusions in this chapter are:

1. **Impact on sectoral and market indices**: The natural disasters show a significant negative impact in FMCG, Consumer durables, Information Technology, Oil & Gas, Metal, and Realty sectors during the natural calamities events, which implies H_{05a} is rejected. A positive impact was found in the Teck and energy sectors, implying H_{05a} failed to be rejected. The positive effect of the overall market index suggests that natural calamities do not significantly depress the Sensex index.
2. **Disaster-specific impact:** The absence of significant negative effects from climatological and hydrological disasters on stock market returns failed to reject null hypotheses H_{05b} and H_{05c}, suggesting that climatological and hydrological disasters do not have a significant negative impact on stock market returns. However, we found geological and metrological disasters have substantial adverse negative effects on stock returns.
3. **Kruskal Wallis test**: The test results showed quantitative similarity to the OLS model findings, providing robustness to the estimated impacts of different natural disasters across various sectors that concern the non-normality in sectoral return distributions.
4. **Extreme trading days:** The examination of extreme trading days provided evidence that the observed market movements were not predominantly attributed to non-disaster factors. The potential influence of natural calamities on the Indian securities market cannot be dismissed entirely.
5. **Cointegration analysis:** The cointegration analysis confirmed the presence of long-run relationships among the variables, allowing the study to utilised the

ARDL model and investigate both long-run and short-run dynamics, including the error correction mechanism that governs the adjustment towards equilibrium after short-term shocks.

6. **Long-run Relationship**: The disaster sentiment proxy exhibited a significant influence on various sectors like capital goods, energy, FMCG, financial services, industrial, and power. This suggests these sectors are more susceptible to impacts of natural disaster calamities.

1. **Short-run Relationship:** The findings revealed that the disaster sentiment proxy (DSI) exerted a more pronounced impact in the short-run compared to the long-run. A significant negative relationship was observed between DSI and sectoral returns across Auto, Capital Goods, FMCG, Financial Services, Industrial, Power, Metals, Oil and Gas, and Realty sectors as a result H_{05d} was rejected. A positive relationship was found in the IT sector, hence H_{05d} is failed to be rejected.

2. **Stability test using COSUM and COSUMSQ**: The stability of the relationship among variables and the impact of sentiment over time, recognizing the potential for investor sentiment and emotions to induce instability and volatility in financial markets. The result provides support to the persistency and heterogeneity role of sentiment in the Indian stock return.

3. **Robustness Test**: Robustness testing confirmed that the predictive power varies considerably across different sectors, indicating that various types of disasters exert distinctly different impacts on stock returns. These findings provide compelling evidence to reject null hypothesis H_{05e}, confirming that disaster sentiment impacts vary significantly across different disaster types.

Overall, this chapter conducts a comprehensive study addressing the impact of natural calamities in the Indian market initially, followed by examination of whether there is a co-movement between this extreme event and the sentiment of the investors. The impacts of natural disasters on financial sentiment represent a more nuanced dimension that current sentiment research has not comprehensively addressed in most of the studies. Incorporating other sentiment indices (implied sentiment) like MMI and VIX (Traditional sentiment), the result provides that there is a significant impact on market reactions due to natural disasters. However, no negative effects were observed in some sectors. The results also suggest that disaster sentiment is a significant driver of stock returns and sectoral impacts, complementing traditional sentiment measures and underscoring the importance of accounting for such event-specific sentiment in market analyses. The analysis highlighted the heightened sensitivity of sectoral returns to disaster sentiment, with the disaster sentiment index exhibiting pronounced negative impacts across multiple sectors in the short term. The same is true for implied sentiment and traditional sentiment measures, such as MMI and VIX, which significantly influence various sectors in stock returns. These findings also reveal that the MMI sentiment proxy serves as a reliable indicator of market sentiment, capturing overall investor sentiment and its implications in various sectors. Nonetheless, it is prudent to consider alternative proxies, such as disaster sentiment, which may potentially capture the nuances of market sentiment within a specific span of time, especially during uncertain events. These results support the validity of the impact of disaster sentiment on stock returns.

Chapter 6: Conclusion and Implication

6.1. Summary and main findings

This thesis investigates the links between theories and hypotheses for formalised theories, with the aim of improving scientific inference by examining the efficacy of two distinct schools of thought. Using long-term data from the BRICS and G5 countries' stock indices between 1990 and 2022, this study examines whether AMH is better off in explaining the behaviour of stock returns than EMH. This study also examined well-established calendar anomalies to investigate their adaptive behaviour in both groups of national indices. Furthermore, this thesis investigates the degree of investor sentiment in the Indian stock market during a period of extreme natural disasters. This thesis is organised into six main chapters: an introductory chapter, a theoretical background chapter, an analysis of time-dependent stock returns in BRICS and G-5 countries, an examination of calendar anomalies and their adaptive effects, an investigation of investor sentiment during natural disasters, and a summary and conclusion section. Apart from the introduction and conclusion, the remaining four chapters comprise the core of this thesis, three of which present the empirical research.

The first chapter of this thesis demonstrates the background and market analysis for the research, grounding its rationale in the necessity for a more comprehensive assessment of AMH in emerging and developed markets. It explores the applicability and problems that arise when examining time-dependent returns, calendar anomalies, and investor sentiment during natural disasters to address gaps in the contemporary financial literature. This chapter outlines the justification of the study and emphasises its primary objectives.

Chapter 2 provides a literature framework covering key areas that lay the foundation for this thesis. The chapter begins with an earlier development of EMH and conferring various stages of development along with forms of EMH, assumptions, and problems that require further examination. The chapter then reviews various stock market anomalies that challenge classical EMH. These anomalies include the value premium, momentum effect, reversal effect, disposition effect, market bubbles, herding behaviour, size effect, and calendar anomalies. Further, trading rules and technical analyses highlighting the conflict between the traditional framework and outperforming stock market returns in the literature are also presented. Confrontations with the assumptions of EMH by BF proponents suggest that investor sentiment plays an important role in shaping the behaviour of financial markets. The AMH emerges as a model that seeks to reconcile the apparent contradictions between the EMH and the BF. The AMH suggests that markets are context-dependent and subject to evolutionary forces, while the EMH and BF coexist in a rationally consistent manner. The literature supporting AMH has become gaining ground, emphasising that markets can differ significantly in terms of their geographical location, operational characteristics, and the size of their respective economies, highlighting the need for further examination of AMH across diverse market settings.

Chapter 3 examines a comparative analysis of the time dependence of stock returns in BRICS and G-5 countries using a comprehensive set of linear and nonlinear tests. The chapter begins with a concise introduction, highlighting the limitations of linear models in capturing complex stock price patterns. This emphasises the need to quantify nonlinearity in stock market behaviour. The text then describes a shift in research approaches, moving from traditional linear modelling techniques to more sophisticated methods that incorporate both linear and nonlinear tests. The chapter then reviews previous empirical research that utilised these tests and highlights the need for continued research that employs a comprehensive set of tests across different market conditions and periods. To quantify the empirical results, this study implements a linear dependency test using autocorrelation, variance ratio, and unit root tests. Subsequently, the return series undergoes a nonlinear test using whitening AR and AR-GARCH methods to eliminate linear correlations. The residuals derived from this process are then subjected to a battery of nonlinear tests, including the McLeod Li, Engle LM, and BDS tests. Following this comprehensive analysis, the observed return behaviours are classified into five predefined categories to examine the behaviour of stock returns. The findings predominantly support the AMH, indicating that market efficiency is not a static condition, but rather a dynamic process characterised by alternating periods of predictability and unpredictability in stock returns. The linear tests signify that the G5 stock markets exhibited behaviour consistent with AMH as compared to BRICS. However, the nonlinear tests consistently uncovered time-varying dependencies in stock returns across all markets, suggesting that AMH provides a more accurate framework for understanding stock market behaviour than the traditional Efficient Market Hypothesis.

Chapter 4 explores calendar anomalies and the adaptive calendar effect through an analysis of well-established seasonal patterns in the financial markets. The chapter begins with a constraint, and the flawed efficient theory was challenged by the existence of stock market anomalies that were documented with theoretical and empirical evidence. This is followed by extensive literature on the day of the week effect, the month of the year, and the turn of the month effect. The literature highlights the need for continuous empirical investigation and consideration using alternative methodologies, time periods, and market contexts to gain a comprehensive understanding of the behaviour of these calendar anomalies over time. To investigate calendar anomalies and their time-varying nature, this study employs models from the GARCH family, specifically utilising both symmetric (GARCH) and asymmetric (EGARCH) specifications. This study examines adaptive calendar anomalies in the market by implementing GARCH models with a three-year rolling fixed window. This approach allows for the analysis of time-varying patterns in the Day-of-the-Week (DOW), Turn-of-the-Month (TOM), and Month-of-the-Year (MOM) effects. The findings show that the Monday effect was found in BRICS countries and that the G5 markets exhibited no significant Monday effect. The January effect was found to be more prevalent in developed countries than in developing countries, and no clear pattern of the MOM effect other than the January effect was found across the stock markets. The turn of the month effect was found to be significant in the BRICS and G5 markets. An empirical analysis examining the time-varying nature of calendar anomalies using a rolling three-year subsample, three out of five in the BRICS market show adaptive calendar anomalies, and developed markets exhibit adaptive market behaviour, oscillating between efficiency and inefficiency across different sub-periods. Furthermore, this study evaluates the profitability of calendar anomalies by comparing returns from a simple buy-and-hold (BH) strategy with those from an implied calendar anomaly trading strategy (ITS). This result suggests that BH produces higher returns than calendar-based ITS strategies in the BRICS markets. Potential profitable trading strategies based on the turn of the month and the sell-in-may trading strategy outperform buy-and-hold in the G5 Market.

The fifth chapter focuses on investor sentiment, an increasingly prominent topic in financial research. This area of study has gained significant traction in recent years, challenging traditional finance theories that assume fully rational market participants. This chapter investigates investor sentiment by examining investor behaviour during natural calamities using the BSE sectoral index data. The first section provides a comprehensive overview of natural disasters, detailing the various types of catastrophic events that occurred during the study period under examination. This is followed by a review of the existing literature pertinent to the research topic, such as geophysical, hydrological, and meteorological effects, as well as the influence of investor sentiment on climate-related disasters and extreme weather events. The third section outlines the methodological approach employed throughout this chapter, with particular emphasis on the complex process of constructing and quantifying investor sentiment, a critical component of the analysis. The empirical findings show that natural calamities have a mixed effect on different sectors. While some sectors such as FMCG, Consumer durables, IT, oil and gas, metal, and reality showed negative impacts, others such as Teck and Energy saw positive effects. The overall market index (Sensex) has a significant positive effect and implies that it has no effect. Furthermore, climatological disasters (e.g., cold waves, avalanches, glacier outbursts, and heat waves) generally have positive effects on sectoral returns. Negative effects have been observed during cyclones, earthquakes, floods, and storms. The second section of the empirical analysis examines the relationship between investor sentiment and sectoral stock returns, showing that disaster sentiment significantly influences sectors such as capital goods, energy, FMCG, financial services, industrial, and power in the long run. In the short run, disaster sentiment has a more pronounced impact on the sectoral index, with significant negative relationships observed in most sectors, except for a positive relationship in the IT sector. Overall, the study found that disaster sentiment is a significant driver of stock returns, complementing other sentiment measures such as the Market Mood Index and Volatility Index.

6.2. Key Findings

Table 6.1: Key findings

Research Objective	Findings
To examine the time dependence of stock return and adaptive market behaviour of return in developed (G-5) and developing (BRICS)	**Linear Autocorrelation test:** Except MOEX, the BRICS and G5 markets experience time varying dependence of stock return. **Linear Variance ratio test**: The BRICS market show an inconclusive result on whether the market is time-dependence. However, the G5 markets show a time varying return dependence **Nonlinear battery test:** All markets under study provided evidence of significant nonlinear dependence in stock returns. **Nonlinear AR-GARCH BDS test**: The findings indicate that both BRICS and G5 markets exhibit behaviour that aligns with the Adaptive Market Hypothesis (AMH)
To examine existence of calendar market anomalies in developed and developing markets	**DOW effect**: The DOW effect was found to be more relevant in developing markets compared to developed markets. **MOY effect**: The MOY effect is widespread in developed market as compared to emerging markets. **TOM effect:** Turn of the month effect was found to be significant in developing and developed markets

To investigate whether calendar anomalies exhibit the potential adaptive market pattern in the markets	Emerging markets like JALSH, MOEX, and SSE showed significant widespread adaptive market anomalies with excess returns, developed markets experienced oscillating between efficiency and inefficiency displayed significant form of episodic anomalies.
To identify which trading strategies, outperform under different market condition	The Buy and Hold trading strategy produce higher returns than ITS strategies in BRICS markets. The SIM and BH strategy outperformed in the G5 market.
To examine the sentiment behaviour of investors in stock market during natural calamities	The result suggests that there is a significant impact on market reaction due to natural calamities. The disaster sentiment proxy exhibited a significant influence on various sectors like capital goods, energy, FMCG, financial services, industrial, and power. A significant negative relationship was observed between DSI and sectoral returns across auto, capital goods, FMCG, financial services, industrial, power, metals, oil and gas, and realty sectors The Disaster Sentiment Index (DSI) exhibited Granger causality for sectors like capital goods, industrial, power, telecommunication, realty, and the overall market index. Overall, this implies sentiment behaviour of investors has a predictive power over returns.

6.2. Concluding Remarks

In conclusion, this comprehensive study provides compelling evidence supporting the Adaptive Market Hypothesis (AMH) across both developed and emerging markets. The research, spanning the BRICS and G5 countries from 1990 to

2022, demonstrates that market efficiency is not a static condition but a dynamic process characterised by alternating periods of predictability and unpredictability in stock returns. The findings reveal that the behaviours of stock returns in G5 markets are more consistent with AMH in linear tests, and nonlinear analyses uncovered time-varying dependencies across all markets, suggesting that AMH offers a more accurate framework for understanding stock market behaviour than the traditional Efficient Market Hypothesis. The investigation of calendar anomalies further supports this adaptive nature, with emerging markets showing more distinct day-of-the-week effects and developed markets displaying stronger month-of-the-year patterns. Notably, the study finds that simple buy-and-hold strategies often outperform calendar-based trading strategies in BRICS markets, whereas certain anomaly-based strategies (TOM and SIM) are profitable in G5 markets. The examination of investor sentiment in the Indian stock market during natural disasters adds another layer to our understanding, revealing that disaster sentiment significantly influences various sectors and has predictive power over returns. These findings collectively underscore the complex and evolving nature of financial markets and the importance of considering both rational and behavioural factors in investment decisions and policymaking. The study contributes valuable insights to the ongoing debate between traditional finance theories and behavioural finance, suggesting that a more significance adaptive approach is necessary for understanding and navigating modern financial markets.

6.3. Novelty of Research and Contribution to Knowledge

This study contributes to the literature on efficient markets, adaptive markets, calendar anomalies, and investor sentiment in several key ways.

- This study examines the validity of AMH in the context of the BRICS and G5 stock markets in an area that has received limited attention in the extant literature. The conceptualisation of efficiency as a time-varying parameter, as proposed by AMH, was explored using linear and nonlinear battery tests. This finding provides empirical support for AMH, validating its concept of market efficiency as a dynamic process that is influenced by changing conditions.
- The analytical scope of this study was expanded by incorporating a diverse range of statistical models. These include more sophisticated approaches, such

as GARCH, EGARCH, ARDL, and causality analysis. By employing this comprehensive suite of methods, this study aimed to address potential biases and enhance the reliability of its findings compared to earlier investigations in the field.

- The thesis also contributes to the literature on calendar anomalies under the AMH. The empirical findings highlight the dynamic nature of calendar anomalies, showing that markets oscillate between periods of efficiency and inefficiency. From a practical standpoint, the adaptive nature of calendar effects can be attributed to behavioural biases, market frictions, geopolitical dynamics, and changing market conditions that the static approach to EMH fails to adequately explain.
- This study makes significant contributions to our understanding of calendar anomalies and their potential to generate excess returns through trading strategies.
- Finally, this thesis provides empirical evidence to support the validity of investor sentiment and stock market dynamics, particularly during extreme natural calamities.

6.4. Implication of the study

The outcome of this study suggests possible practical implications for various stakeholders in financial markets.

6.4.1. For Institutional investment and retail investors

1. The study documented that the market undergoes different periods of return efficiency and inefficiency. Thus, market participants should be treated or viewed in different ways. Techniques such as market timing, sectoral rotation, and security selection should be used by institutional or retail investors in diverse market environments subject to specialist concepts.
2. The findings also document that time-varying return predictability, suggesting arbitrage opportunities, arise in financial markets from time to time, and investors must be aware of these possibilities to earn abnormal returns.

3. Empirical evidence suggests that market performance can vary significantly across different environments. This heterogeneity in market behaviour underscores the importance of a market-specific analysis for retail investors. In order to mitigating risks associated with changing market conditions, it would be prudent for investors to adopt adaptive investment strategies that can adapt to fluctuations in market efficiency and the evolution of calendar anomalies.

4. The result of the finding suggests that disaster sentiment as a significant driver of stock market returns. In addition to the market mood index and volatile index, it is prudent to consider the Google search volume index as a proxy indicator of market sentiment.

5. The empirical evidence suggests that a buy-and-hold strategy has demonstrated superior performance across a majority of market conditions. This study reveals that reliance on technical analysis and specific trading strategies for predicting return movements may prove ineffective in yielding the desired outcomes. A hybrid approach combining the long-term stability of a buy-and-hold strategy with sentiment-informed adjustments may be optimal.
6. Institutional investor managers should adopt a balanced approach that emphasises both survival strategies and profit maximisation when conducting targeted market analyses. By implementing this approach, institutional managers can better navigate market complexities, mitigate risks, and capitalise on market inefficiencies, while ensuring their institution's long-term viability.

6.4.2. For Policymarker

1. Policymakers should integrate investor sentiment analysis into regulatory frameworks by employing a dual approach to address both rational and emotional market behaviours. This includes the implementation of a sentiment monitoring system that utilises advanced analytics to track real-time investor mood shifts and design flexible regulatory mechanisms that respond to significant changes in sentiment.

2. The dynamic nature of market efficiency suggested by AMH requires more flexibility with tightened information disclosure and timeliness information, along with taking policy measures to control the volume flow of institutional investors that reduce the wavelength of price movement. to mitigate the excessive price volatility. The AMH perspective emphasizes that market behavior adapts differently requiring tailored interventions rather than rigid rules.
3. The significance of market inefficiency in eliciting trader strategies and its dynamic nature in shaping regulatory frameworks provides valuable insights for policymakers, enabling them to adapt to financial innovations and foster economic development through the implementation of evidence-based policies derived from analyses of market efficiency evolution.
4. Regulatory can educate investors about anomalies to reduce irrational trading. Retail investors often follow seasonal trends, requiring attention to predispositions that influence market dynamics and trading behaviour.
5. Policymakers should require strict reporting to identify market distortions, strengthen circuit breakers during turbulence, and mandate alternative trading systems like batch auctions to enhance market stability.
6. The January Effect, which is linked to tax-loss selling in December, suggests that tax incentives may result in predictable trading behaviours. Policymakers could reconstruct tax regulations to mitigate distortions in the market

6.5. Limitations of the study

Despite achieving its objectives, this study acknowledges inherent a number of limitations.

1. The sample periods for the observed markets differ in length because of data availability constraints. Two market from emerging markets (MOEX and JALSH), lack sufficient historical data to cover the intended sample period.
2. The study’s focus on a limited number of emerging markets, excluding key emerging market such as Thai, Vietnam, and Hong Kong stock markets, may lead to potential biases and an incomplete representation of the broader emerging market landscape.

3. A relatively shorter time frame compared to earlier studies, such as those by Kim et al. (2011) and Urquhart (2013), used significantly longer data over a period of 100 years. The study is limited to 32 years' timeframe, a longer timeframe allows more market events and economic cycles, and the potential yields more robust results.
4. A fixed three-year rolling window is used to analyse time-varying efficiency and calendar anomalies. The window size was chosen to balance short-term fluctuations and statistical robustness, the chosen three-year window, may not capture a subtle distinction of market behaviours across different time scales.
5. The reliance on the Google sentiment index to gauge investor sentiment may not fully represent the entire investor population and could be influenced by factors unrelated to genuine investment intent, potentially affecting the accuracy and generalisability of the findings.

6.6. Suggestion for further studies

Future research on AMH holds significant potential due to its recent emergence and growing relevance in finance. Future studies could develop a quantitative framework to measure and predict market adaptability across various asset classes and examine context-specific market behaviours. Longitudinal studies can be tested across different markets over extended timeframes and analyse market efficiency dynamics in response to economic, technological, and social changes. Evaluate whether advanced machine learning techniques can predict market adaptations, as proposed by AMH, by incorporating algorithms to analyse large datasets on market behaviours, investor sentiment, and macroeconomic indicators. Additionally, further study can investigate adaptive investment strategies that dynamically adjust to market conditions using real-time data and AI-driven decision-making. This could validate the AMH and offer practical applications for investors and policymakers in complex global financial markets. Furthermore, it is recommended that advanced sentiment analysis be incorporated into financial modelling, the impact of exogenous events on market adaptation be assessed, and interdisciplinary approaches be explored. Moreover, the influence of emerging financial technologies and the necessity for long-term studies on market evolution should be addressed with broadly and generalizable.

APPENDICES

Appendix – I

Table. 1: Ljung-Box statistics for the BRICS markets daily returns

Panel A: India (BSE Sensex)					
	AR	5	10	15	20
Full Sample	17	0.011	0.020	0.095	5.049
1990-1992	0	5.640	9.760	7.414	20.072
1993-1995	2	2.532	8.657	13.165	19.008
1996-1998	3	1.164	6.908	14.195	25.235
1999-2001	1	5.272	12.879	16.011	26.913
2002-2004	4	0.469	3.765	9.228	12.877
2005-2007	2	0.353	7.319	13.357	20.568
2008-2010	1	3.892	14.335	16.386	25.364
2011-2013	3	0.059	1.840	9.206	12.963
2014-2016	3	1.546	6.534	7.864	11.175
2017-2019	3	1.401	12.388	16.116	20.306
2020-2022	7	0.804	1.802	10.327	20.119
Panel B: China (SSE Composite)					
	AR	5	10	15	20
Full Sample	15	0.005	0.024	0.154	5.008
1990-1992	0	8.605	16.510	19.623	23.912
1993-1995	6	0.332	8.343	14.245	18.634
1996-1998	9	0.006	0.606	18.699	26.852
1999-2001	3	0.256	7.848	25.812	37.966
2002-2004	0	0.926	5.178	7.414	12.304
2005-2007	6	0.176	1.616	21.206	29.201
2008-2010	0	3.403	5.813	14.110	17.931
2011-2013	0	2.069	11.559	13.876	15.897
2014-2016	8	0.225	3.505	6.430	25.832
2017-2019	7	0.094	3.244	7.929	11.443
2020-2022	1	3.540	6.917	9.538	12.377
Panel C: Brazil (IBVESPA)					
	AR	5	10	15	20
Full Sample	3	1.375	3.195	6.517	14.591
1990-1992	0	1.476	1.604	1.802	1.983
1993-1995	9	0.453	1.412	13.207	18.841
1996-1998	9	0.132	3.406	5.941	17.784
1999-2001	5	0.276	6.243	13.196	15.730
2002-2004	0	2.758	9.877	13.903	23.169
2005-2007	0	5.180	8.576	11.916	17.937
2008-2010	3	0.095	7.789	10.125	19.650
2011-2013	0	0.855	3.084	9.051	16.208
2014-2016	1	3.316	9.567	11.013	12.315
2017-2019	7	0.013	0.727	1.972	6.732

2020-2022	8	0.250	0.634	10.698	20.489
Panel D: South Africa (JALSH)					
	AR	5	10	15	20
Full Sample	7	0.0066	1.6135	6.7152	23.154
1993-1995	1	3.1759	15.871	21.22	24.363
1996-1998	4	0.6179	4.9236	17.587	20.059
1999-2001	2	2.153	6.0382	11.769	15.006
2002-2004	3	0.3047	2.2029	4.2449	6.1153
2005-2007	0	5.4311	6.3691	18.203	23.889
2008-2010	3	1.3037	5.987	10.035	16.176
2011-2013	0	8.2979	13.894	19.655	26.603
2014-2016	2	2.6467	4.0756	7.0245	12.782
2017-2019	0	2.5735	11.756	15.642	22.807
2020-2022	8	0.0275	0.3597	4.6507	27.523
Panel E: Russia (MOEX)					
	AR	5	10	15	20
Full Sample	14	0.013	0.039	0.424	16.562
1996-1998	1	6.820	9.248	11.601	27.058
1999-2001	1	4.155	11.527	17.058	24.585
2002-2004	3	0.562	3.110	9.094	11.036
2005-2007	1	2.730	4.036	18.553	19.561
2008-2010	1	3.891	9.516	32.764	40.370
2011-2013	0	4.865	9.442	12.068	19.386
2014-2016	0	1.757	5.591	10.136	14.607
2017-2019	0	8.046	10.181	17.089	22.468
2020-2022	1	3.247	11.555	15.052	20.389
Source: *Author's computation Using EViews*					

Table. 2: Ljung-Box statistics for the G5 markets daily returns

Panel A: France (CAC 40)					
	AR	5	10	15	20
Full Sample	6	0.005	2.430	6.905	18.946
1990-1992	5	0.022	10.332	14.699	23.047
1993-1995	0	3.524	12.100	12.196	13.039
1996-1998	7	0.064	3.202	7.871	17.203
1999-2001	2	0.541	8.297	13.432	18.950
2002-2004	6	0.080	7.781	20.455	29.428
2005-2007	1	2.206	6.686	7.783	11.160
2008-2010	5	0.149	7.376	11.235	15.068
2011-2013	5	0.021	2.343	7.015	8.949
2014-2016	5	0.037	2.521	9.063	14.666
2017-2019	0	2.537	5.249	11.512	18.234
2020-2022	8	0.024	0.262	8.637	22.594
Panel B: Germany (DAX 30)					

	AR	5	10	15	20
Full Sample	6	0.006	0.359	8.439	20.691
1990-1992	0	3.689	14.375	18.576	20.569
1993-1995	0	5.811	15.603	25.608	26.528
1996-1998	7	0.108	4.763	14.643	27.749
1999-2001	0	2.817	8.789	10.742	28.850
2002-2004	1	4.309	9.778	5.022	5.014
2005-2007	0	4.615	6.756	7.118	12.814
2008-2010	4	1.122	6.839	9.217	17.321
2011-2013	5	0.023	3.400	13.115	17.032
2014-2016	5	0.095	5.000	11.292	16.101
2017-2019	0	6.633	9.280	15.005	17.747
2020-2022	8	0.060	0.385	4.341	20.394
Panel C: United Kingdom (FTSE 100)					
	AR	5	10	15	20
Full Sample	17	0.009	0.032	0.073	5.229
1990-1992	7	0.093	7.737	16.127	23.350
1993-1995	0	0.889	6.108	15.783	17.962
1996-1998	9	0.431	1.996	17.809	23.925
1999-2001	2	1.672	4.297	10.158	18.396
2002-2004	7	0.056	3.208	5.945	10.100
2005-2007	1	5.191	8.242	14.590	15.994
2008-2010	9	0.282	2.423	8.606	12.819
2011-2013	0	6.422	9.730	11.603	14.907
2014-2016	5	0.055	3.262	11.717	21.180
2017-2019	0	2.329	5.977	7.015	8.422
2020-2022	8	0.056	0.613	14.633	24.298
Panel D: Japan (Nikkei 225)					
	AR	5	10	15	20
Full Sample	2	2.262	8.354	13.691	21.854
1990-1992	2	0.448	8.719	13.172	17.499
1993-1995	0	5.827	7.430	17.476	28.166
1996-1998	4	0.685	8.912	13.849	23.201
1999-2001	1	1.188	11.124	13.868	16.477
2002-2004	0	1.005	10.334	13.911	16.948
2005-2007	1	6.091	10.457	12.776	17.205
2008-2010	1	6.089	10.352	14.197	19.197
2011-2013	9	0.080	3.845	10.539	15.531
2014-2016	1	3.951	5.437	13.368	16.948
2017-2019	1	4.796	12.817	17.227	25.235
2020-2022	3	0.773	9.726	17.579	25.719
Panel E: U.S (S&P 500)					

	AR	5	10	15	20
Full Sample	18	7.850	12.634	8.554	16.770
1990-1992	1	1.533	8.522	15.514	19.246
1993-1995	0	7.850	12.634	28.554	36.770
1996-1998	0	2.435	11.328	13.897	33.464
1999-2001	5	0.045	3.351	15.680	24.547
2002-2004	0	0.947	9.912	17.785	33.672
2005-2007	1	4.253	16.482	20.397	23.895
2008-2010	3	0.569	3.841	10.204	22.800
2011-2013	5	0.094	8.052	13.607	23.363
2014-2016	0	4.644	8.124	15.575	21.479
2017-2019	8	0.032	1.925	10.155	20.263
2020-2022	9	0.043	1.263	2.714	4.156
Source*: Author's computation Using EViews*					

Appendix -II

Table 3: The estimated result of Month of the year effect using GARCH Model in all the markets under examination

Panel A: Mean Equation

	SSEC	IBOVESPA	JALSH	MOEX	SENSEX	CAC 40	DAX 30	FTSE 100	NIKKEI 225	S&P 500
January	**0.082**	0.042	0.031	0.081	-0.051	-0.011	-0.002	-0.054	-0.068	0.005
February	***0.136***	0.039	0.028	-0.032	-0.051	0.045	**0.072**	0.008	0.022	0.043
March	-0.008	-0.001	**-0.061**	-0.027	-0.008	-0.016	0.055	-0.027	0.032	0.055
April	-0.039	0.009	0.050	0.043	0.009	0.038	**0.081**	**0.086**	-0.003	0.017
May	-0.038	-1.379	-0.059	-0.077	0.002	0.001	**0.067**	0.005	-0.011	-0.001
June	0.000	-0.686	-0.050	-0.041	-0.016	-0.066	**-0.098**	**-0.062**	-0.012	**-0.049**
July	0.014	-0.003	0.014	-0.015	0.045	0.018	0.020	0.026	-0.047	0.019
August	-0.015	**-0.125**	-0.032	0.045	0.037	***-0.124***	**-0.073**	-0.001	-0.048	-0.021
September	-0.047	-0.044	**-0.059**	-0.028	0.004	***-0.170***	-0.021	**-0.063**	-0.001	-0.048
October	0.000	-0.101	**0.078**	-0.032	-0.012	0.020	-0.014	0.016	0.039	0.016
Novermber	0.029	**0.100**	0.019	0.012	0.023	0.042	0.001	0.004	0.030	**0.047**
December	0.017	0.076	0.060	**0.102**	0.015	0.042	0.028	**0.075**	0.062	0.008

Panel B: Variance equation

	SSEC	IBOVESPA	JALSH	MOEX	SENSEX	CAC 40	DAX 30	FTSE 100	NIKKEI 225	S&P 500
January	0.005	***0.372***	0.009	0.009	**0.022**	0.006	0.007	***0.019***	0.009	***0.022***
February	0.004	**-0.088**	0.001	***0.028***	***0.029***	0.004	0.010	0.005	0.012	0.004
March	**-0.015**	***0.314***	0.004	-0.016	0.003	0.001	-0.001	-0.004	**0.018**	0.004
April	**0.020**	***-0.336***	-0.006	-0.004	-0.008	-0.006	-0.001	-0.005	**0.020**	-0.005
May	***0.032***	***-0.582***	0.004	-0.003	-0.013	0.000	-0.007	-0.001	**-0.019**	-0.003
June	-0.011	-0.369	-0.012	**-0.019**	**-0.016**	0.006	0.004	0.011	-0.008	0.003
July	-0.006	***-0.666***	**-0.016**	-0.010	***1.615***	-0.003	0.002	-0.011	-0.010	**-0.019**
August	-0.012	***-0.652***	0.003	-0.015	-0.002	0.006	0.005	-0.001	-0.001	-0.005
September	-0.004	-0.022	0.001	**0.024**	**0.016**	-0.005	-0.003	**0.013**	0.009	0.008

October	***0.987***	***0.820***	0.001	0.008	-0.016	-0.002	-0.010	-0.009	-0.001	0.000
November	***0.984***	0.021	0.006	-0.006	-0.014	0.004	0.001	-0.001	-0.001	-0.008
December	0.001	***-0.614***	0.002	0.006	-0.004	-0.006	0.004	**-0.013**	0.006	-0.008
Panel C: Diagnostic test										
	SSEC	IBOVESPA	JALSH	MOEX	SENSEX	CAC 40	DAX 30	FTSE 100	NIKKEI 225	S&P 500
GED	1.0101	1.44042	1.44045	1.284796	1.437242	1.47957	1.398801	1.435642	1.432107	-13635.63
LLR	-13980.6	-27096.59	-10106.48	-12053.52	-13342.85	-13014.1	-14682.33	-10977.33	12987.5	-10762.14
ARCH-LM	0.013309	0.230092	0.025	1.963921	0.092209	1.93906	1.244044	0.001172	0.089548	0.043495
Q (10)	0.1436	0.8507	0.6651	0.7517	0.747	0.3481	0.2976	0.973	0.533	0.219
Q^2(10)	0.705	0.356	0.415	0.386	2.113	0.555	0.585	0.114	0.924	0.741

Source*: Author's computation Using EViews*

Note(s): The table represent the result of the MOY effect on both return and conditional variance using GARCH and EGARCH estimation. Bold italic, Bold and bold underlined indicate significance at the 1%, 5% and 10% levels respectively. ω, α, β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q (10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, Q2(10) =Box-pierce Q2 statistics for serial correlation at the 5 percent level of the order 10 lag,

Table 4: The estimated result of Month of the year effect using EGARCH Model in all the markets under examination

Panel A: Mean Equation										
	SSEC	IBOVESPA	JALSH	MOEX	SENSEX	CAC 40	DAX 30	FTSE 100	NIKKEI 225	S&P 500
JANUARY	**0.082**	0.042	0.031	0.081	-0.058	-0.015	-0.011	-0.040	-0.068	0.005
FEBRUARY	***0.136***	0.039	0.028	-0.022	-0.055	**0.072**	0.045	0.008	0.022	0.043
MARCH	-0.008	-0.001	-0.061	-0.027	-0.008	0.055	-0.016	-0.027	0.008	-0.038
APRIL	-0.039	0.051	0.050	0.043	0.009	**0.081**	0.038	0.029	0.071	0.055
MAY	-0.038	-0.049	-0.059	-0.077	0.002	**0.025**	0.001	0.005	-0.011	-0.001
JUNE	0.000	-0.251	-0.050	-0.041	-0.016	**-0.098**	-0.066	**-0.062**	-0.012	**-0.049**
JULY	0.014	**-0.125**	0.014	-0.015	0.045	0.019	0.018	0.026	-0.002	0.019
AUGUST	-0.015	-0.044	-0.032	0.045	0.037	**-0.073**	***-0.124***	-0.001	-0.066	-0.021
SEPTEMBER	-0.047	-0.101	-0.059	-0.028	0.004	-0.021	-0.039	**-0.063**	-0.001	**-0.048**
OCTOBER	0.000	**0.100**	**0.078**	-0.032	-0.012	-0.014	0.020	0.016	0.039	0.016
NOVERMBER	0.029	0.076	0.019	0.012	0.023	0.001	0.042	0.004	0.030	**0.047**
December	0.017	0.100	0.060	**0.102**	0.015	0.028	0.042	**0.075**	0.062	0.008
	Variance									
	SSEC	IBOVESPA	JALSH	MOEX	SENSEX	CAC 40	DAX 30	FTSE 100	NIKKEI 225	S&P 500
JANUARY	**0.082**	0.042	0.009	0.009	0.022	0.006	0.007	***0.019***	0.009	**0.022**
FEBRUARY	***0.136***	0.039	0.001	0.028	0.029	0.004	0.010	0.005	0.012	0.004
MARCH	-0.008	-0.001	0.004	-0.016	0.003	0.001	-0.001	-0.004	0.032	0.004
APRIL	-0.039	0.051	-0.006	-0.004	-0.008	-0.006	-0.001	-0.005	**0.020**	-0.005
MAY	-0.038	-0.049	0.004	-0.003	-0.013	0.000	-0.007	-0.001	-0.019	-0.003
JUNE	0.000	-0.251	-0.012	**-0.019**	**-0.016**	0.006	0.004	0.011	-0.008	0.003
JULY	0.014	**-0.125**	**-0.016**	-0.010	0.000	-0.003	0.002	-0.011	-0.010	**-0.019**
AUGUST	-0.015	-0.044	0.003	-0.015	-0.002	0.006	0.005	-0.001	-0.001	-0.005
SEPTEMBER	-0.047	-0.101	0.001	***0.024***	**0.016**	-0.005	-0.003	**0.013**	0.009	0.008

OCTOBER	0.000	**0.100**	0.001	0.008	-0.016	-0.002	-0.010	-0.009	-0.001	0.000
NOVERMBER	0.029	0.076	0.006	-0.006	-0.014	0.004	0.001	-0.001	-0.001	-0.008
December	0.017	0.100	0.002	0.006	-0.004	-0.006	0.004	**-0.013**	0.006	0.000
Panel C: Diagnostic test										
GED	1.005	1.295123	1.480819	1.282807	1.440441	1.47957	1.398801	1.434292	1.431741	1.353914
LLR	13,981.10	18510.2	10051.15	12049.33	13318.65	13014.1	13055.22	10974.27	13636.4	10760.59
ARCH-LM	0.013	1.560583	2.250382	0.766429	2.03649	0.314923	1.244044	0.000123	0.005287	0.108924
Q (10)	0.125	1.2072	0.160	0.095	2.0374	0.262	0.0259	1.6002	0.3516	0.109
$Q^2(10)$	5.153	6.861	1.979	8.611	6.7555	1.262	5.243	8.8062	1.4264	6.3111

Source*: Author's computation Using EViews*

Note(s): The table represent the result of the MOY effect on both return and conditional variance using GARCH and EGARCH estimation. Bold italic, Bold and bold underlined indicate significance at the 1%, 5% and 10% levels respectively. ω, α, β, and γ represent constant, ARCH effect, GARCH effect and asymmetric leverage effect respectively. GED= Generalised error distribution estimated using EViews Legacy, LLR= Log-likelihood value, ARCH-LM = Heteroscedasticity test at lag 1, Q (10) = Ljung-Box statistics for serial correlation at the 5 percent level of the order 10 lag, Q2(10) =Box-pierce Q2 statistics for serial correlation at the 5 percent level of the order 10 lag,

Appendix -III

Table 5: View of the spreadsheet showing the computation of trading strategy on calendar anomalies (Monday effect)

	A	B	C	D	E	F	G	H
	Date	Close	Return	Day of the week	Monday	Friday	Buy on Monday	Sell Friday
1	01/01/1990	783.35	0	=WEEKDAY(A2,2)	=IF(D2=1,1,0)	=IF(E2=1,0,1)	=IF(E2=1,C2,0)	=IF(F2=1,C2,0)
2	02/01/1990	780.01	=LN(B3/B2)	=WEEKDAY(A3,2)	=IF(D3=1,1,0)	=IF(E3=1,0,1)	=IF(E3=1,C3,0)	=IF(F3=1,C3,0)
3	"	"	"	"	"	"	"	"
4	"	"	"	"	"	"	"	"
...	...	...	...	...	...	...	...	....
7980	30/12/2022	774.58	=LN(B7980/B7979	=WEEKDAY(A7980,2)	=IF(D7980=1,1,0)	=IF(E7980=1,0,1)	=IF(E7980=1,C7980,0)	=IF(F7980=1,C7980,0)

Table 6: View of the spreadsheet showing the computation of trading strategy on calendar anomalies (January effect effect)

	A	B	C	D	E	F	G	H
	Date	Close	Return	Month	January	December	Buy on Jan	Sell Dec
1	01/01/1990	783.35	0	=MONTH(A2)	=IF(D2=1,1,0)	=IF(D2=12,1,0)	=IF(E2=1,C2,0)	=IF(F2=1,C2,0)
2	02/01/1990	780.01	=LN(B3/B2)	=MONTH(A3)	=IF(D3=1,1,0)	=IF(D3=12,1,0)	=IF(E3=1,C3,0)	=IF(F3=1,C3,0)
3	"	"	"	"	"	"	"	"
4	"	"	"	"	"	"	"	"
...	...	...	...	...	...	...	...	....
7980	30/12/2022	774.58	=LN(B7980/B7979	=MONTH(A7980)	=IF(D7980=1,1,0)	=IF(E7980=1,0,1)	=IF(E7980=1,C7980, 0)	=IF(F7980=1,C7980, 0)

Table 5: View of the spreadsheet showing the computation of trading strategy on calendar anomalies (Turn of the Month effect)

	A	B	C	D	E	F
	Date	Close	Return	Month	Day of the month	TOM
1	01/01/1990	783.35	=LN(B2/B1)	=MONTH(A2)	=IF(D3=D2,E2+1,1)	=IF(E3<=1,1,IF(D2=D8,0,1))
2	02/01/1990	780.01	=LN(B3/B2)	=MONTH(A3)	=IF(D4=D3,E3+1,1)	=IF(E4<=1,1,IF(D3=D9,0,1))
3	"	"	"	"	"	"
4	"	"	"	"	"	"
7980	30/12/2022	774.58	=LN(B7980/B7979	=MONTH(A7980)	=IF(D7980=D7979,E7979+1,1)	=IF(E7980<=1,1,IF(D7980=D7981,0,1))

Table 7: Computation of Implied trading strategy and Buy and Hold Strategy

Year Frac	=YEARFRAC(A2,A7891)
Exposure time	=J5/COUNTA(D2:D7891)
SD	=STDEV.S(C3:C7891)
SD Rule	=STDEV.S(G2:G7891)
SD B&H	=STDEV.S(H2:H7891)
ITS trade	=COUNTIF(F3:F7980,1)
Buy and Hold strategy	=SUM(C2:C7980)
ITS Strategy	=SUM(H2:H780)
Difference	=J7-J8
Annualised Different	=((J8/J7)^K13)
	=J13-1

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- Presented a paper entitled *Fintech: Opportunities and Challenges Beyond the Post Covid world,* in international conference on “Standardizing Management Practices: Challenges and Opportunities” held on 12 – 14 August 2021.
- Presented a paper entitled Are *the markets an Adaptive market? Empirical evidence from emerging market (Indian stock market,* in International Conference on the “Changing Global Economic Landscape: Sustainable Strategies for the New Normal” held on 23 March 2022.
- Presented a paper entitled *The Disappearing Holiday Effect: Evidence from the Indian Stock Index* in International Conference on “Contemporary Issue in Emerging Market (CIEMC, 2022)” held on 28-29 October, 2022.
- Presented a paper entitled *Stock market anomalies during religious holidays: An insight on Indian stock market* in 6th Annual Conference of North East India Commerce and Management Association held at Shillong College on 5-6 May, 2023.
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Workshop attended:

- 2021: Participate on "Making Frugal Innovation Work" held on 13th Oct., 2021 organised by Department of Management, Mizoram University
- 2021: Participate in "online Conference on Innovation and Entrepreneurship Development" held on 27-28 February. Technology innovation and Incubation centre, Gwalior
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ABSTRACT

AN EMPIRICAL ANALYSIS OF THE ADAPTIVE MARKET HYPOTHESIS, MARKET ENVIRONMENT AND INVESTORS SENTIMENT IN NATURAL CALAMITIES

AN ABSTRACT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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Introduction

The domain of finance has long been dominated by traditional theories, particularly the Efficient Market Hypothesis (EMH), which has been a focal point of research and debate since the mid-20th century. The Efficient Market Hypothesis, as formalized by Fama (1970), posits that financial markets are "informationally efficient," with security prices accurately reflecting fundamental intrinsic values. This theory suggests that market prices rapidly incorporate new information, making it impossible for investors to consistently outperform the market. However, despite extensive research spanning over five decades, there remains no consensus among economists regarding market efficiency (Worthington & Higgs, 2005; Borges, 2010; Baker & Wurgler, 2007; Parulekar, 2017; Woo et al., 2020). The occurrence of market bubbles, which seems incompatible with the notion of consistently efficient markets. The assumption of universal investor rationality, fails to account for varying levels of expertise and decision-making processes among market participants. The limitations of arbitrage, which traditional theory suggests should counteract irrational trading but often falls short in practice.

In response to the limitations of the EMH, Behavioural finance has become increasingly popular, challenging the assumption of purely rational decision-making in traditional finance models. Proponents of behavioural finance argue that investors are subject to cognitive and emotional biases, leading to seemingly irrational behaviour (Shefrin & Statman, 1985; Shleifer and Vishny, 1997; Barber and Odean, 2001; Shiller 2003). This approach has provided insights into various market phenomena, including noise trading (Black, 1986; Zargar & Kumar, 2019), market anomalies (Águila, 2009), and the influence of investor sentiment on market prices (Shiller, 2000, 2015).

The detection of market anomalies has further challenged the EMH, with studies showing that certain trading strategies can yield above-average returns (Rozeff & Kinney, 1976; De Bondt & Thaller, 1987; Greenwald et al., 2004; McConnell & Xu, 2008; Wang et al., 2013; Auer & Rottmann, 2019; Komariah & Ramadhan, 2022). Behavioural finance researchers have attributed these anomalies to psychological factors such as overreaction and underreaction in the market (Sharma & Narayan, 2014), market bubbles (Kapoor, 2017), and other behavioural biases (Narayan and Zheng, 2010; Deyshappriya, 2014; Farag, 2013). However, proponents of the EMH have countered these arguments, suggesting that behavioural biases and market inefficiencies only arise under specific conditions, such as during bubbles, crashes, or other market frictions (Fama, 1998; Malkiel, 2003; Kartašova et al., 2014; Mishra et al., 2015; Baberis, 2018; Patton & Weller, 2020).

The ongoing discussion between conventional finance and behavioural finance has resulted in the emergence of fresh theories aimed at reconciling these opposing viewpoints. One such hypothesis is the notion of bounded rationality suggested by Simon (1955), which asserts that the stock market is neither entirely efficient nor ineffective. Expanding on this notion, Campbell et al. (1998) introduced a comparative methodology for assessing market efficiency, proposing that financial markets ought to be assessed in relation to one another rather than in absolute terms. A significant breakthrough in this reconciliation effort came with Lo's (2004) introduction of the Adaptive Market Hypothesis (AMH). The AMH provides a new theoretical framework that integrates elements of both the EMH and behavioural finance. This hypothesis posits that market efficiency is not a fixed state but an evolving condition influenced by environmental factors and the adaptability of market participants. Lo (2004) argues that "price reflects as much information as dictated by the combination of environmental conditions and the number and nature of species in the economy," where "species" refers to groups of market participants with similar behaviours, such as hedge funds, mutual funds, and pension funds.

The Adaptive Market Hypothesis

The AMH's theoretical foundation draws from principles of evolutionary biology and bounded rationality, offering a more nuanced and dynamic perspective on market behaviour. The methodology is grounded in the seminal work of Wilson (1975) in the field of evolutionary psychology, which applies the principles of competition, reproduction, and natural selection to social interactions. This evolutionary perspective is rooted in “evolutionary biology” rather than the laws of physics that govern the rational behaviours of the market (Lo, 2004). The AMH integrates concepts like competition, mutation, reproduction, and natural selection to create a comprehensive perspective of the market that amalgamates the tenets of traditional finance with insights from behavioural finance (Lo, 2005). Lo (2004) described the AMH as a new theory and successor to the EMH, which incorporates behavioural alternatives derived from an "evolutionary principle." The theoretical framework aims to merge EMH with behavioural aspects by utilizing concepts of bounded rationality and relevant environmental aspects, drawing from Simon's (1955) psychological aspects of learning. Notably, EMH assumes frictionless markets, whereas AMH relies on dynamic market conditions.

Market anomalies

The term "anomaly" is gaining prominence in economics, particularly in finance literature can be traced back to 1975, as seen in Gentry's (1975) article "Capital Market Line Theory, Insurance Company Portfolio Performance, and Empirical Anomalies." An anomaly refers to something odd or deviating from the norm. Frankfurter and McGoun (2001) describe it as an irregularity or deviation from the natural order. Anomalies indicate market inefficiency, fostering new, successful ideas and theories. Financial market anomalies differ; initially, they highlighted deviations from traditional finance concerning asset pricing and market efficiency. Later, they were applied to behavioural finance literature. Tversky and Kahneman (1986) define market anomalies as deviations from accepted paradigms that are too widespread to ignore, too systematic to dismiss as random error, and too fundamental to accommodate by relaxing the normative system.

The observed deviations from the assumptions of market efficiency have given rise to a crucial new field in finance: Behavioural Finance (BF). BF acknowledges the presence of cognitive biases, heuristics, and irrational behaviour among market participants, which can lead to systematic deviations from rational expectations and utility maximisation principles underlying traditional asset pricing models (Barberis & Thaler, 2003; Shiller, 2003). Behavioural finance presents a more intricate perspective on market abnormalities, illuminating occurrences that question the legitimacy of the EMH (Hirshleifer, 2001; Baker & Wurgler, 2007). For instance, the value premium anomaly, where value stocks tend to outperform growth stocks, can be attributed to the anchoring bias and the disposition effect, which lead investors to hold onto losing stocks too long and sell winning stocks too soon (Barberis et al, 2002; Frazzini, 2006). This implies empirical evidence of market anomalies seem to contradict traditional theories of asset-pricing behaviour and also plays a crucial role in identifying potential market inefficiencies. Market anomalies indicate the existence of profit opportunities, suggesting market inefficiency or flaws in the asset-pricing models used to explain price movements (Latif et al., 2011; Caporale et al., 2017; Woo et. al., 2020).

The Calendars Anomalies

Calendar anomalies refer to the observed patterns or regularities in stock returns that are related to specific calendar periods, defying the efficient market hypothesis (EMH). These anomalies suggest that stock returns exhibit predictable tendencies, either higher or lower, depending on factors such as the day of the week, the day of the month, or the month of the year. The origins of calendar anomalies can be traced back to the 1930s, Kelly (1930) found that Monday was a worse day to buy a stock. Cross (1973) was the first to conduct academic study that took into account the fact that the Monday effect tends to show the lowest stock returns as compared to other days.

Another literature of anomalies is month-of-the-year anomalies, the earliest documented reference to a month-of-the-year effect is credited to Wachtel (1942), who observed the "January effect" – the tendency of stock prices to rise more in January than in other months, particularly for small-capitalization stocks. The well-known studies on the month-of-the-year effect conducted by Rozeff and Kinney (1976) gained attention to practitioners and academics, who found that average stock returns in the NYSE were significantly higher in January (3.48%) compared to other months of the year (0.42%). The tax-loss selling hypothesis has been widely accepted as a theoretical explanation for the January effect. This hypothesis suggests that investors engage in tax-loss selling towards the end of the year to realize losses for tax purposes. Subsequently, they rebalance their portfolios in January, contributing to the observed higher stock returns during that month (Ritter, 1988; Dahlquist & Sellin, 1994).

One of the notable anomalies that have been observed in financial markets is the turn-of-the-month effect. This anomaly refers to the tendency for stock prices to exhibit higher returns around the turn of the month, specifically during the last trading day of the current month and the first few trading days of the following month. Ariel (1987) in a seminal study on the US stock market exhibited persistent and statistically significant outperformance compared to the returns for the entire month. Lakonishok and Smidt (1988) corroborated the existence of the turn-of-the-month effect and proposed that it could be linked to the timing of monthly salary payments and the subsequent reinvestment of funds by individual investors. Several studies on market anomalies like Narayan and Zheng, (2010) in Chinese stock market, Farag (2013) in Emerging market, Deyshappriya (2014) in Colombia stock exchange, Ahmed and Boutheina (2017) in Tunisia stock market provides an evidence of market anomalies in calendar effect across different stock market. Meanwhile, Rossi and Gunardi, (2018) do not show strong proof of calendar effect. Market anomalies have not occurred all time (Chalamandaris, et al., 2021). Others studies also suggest that this market anomalies appear not in all time but at least to a large extent (Engelberg et al., 2018; Wahal, 2019).

The sentiment of Investor

Investor sentiment has gained significant attention in financial market research, with academics exploring its impact on stock returns, market volatility, and its measurement and incorporation into financial models. Sentiments encompassing feelings, thoughts, attitudes, emotions, and ideas about a situation significantly influence investor opinions (Mittal & Goel, 2012). Early studies indicate that sentiment is linked to the formation of speculative bubbles (Smidt, 1968), biased expectations among market participants (Zweig, 1973), noise in financial markets (Black, 1986), deviations from normative expectations (Cliff & Denis, 2004), and waves of optimism and pessimism (Baker & Wular, 2006).

Academic believes investor sentiment has the potential to influence stock market returns and existing literature concentrates on the impact of sentiment on returns and volatility. Wysocki (1998) investigated the factors influencing the web posting volume of messages on stock message boards and the impact on stock trading volume and return. He found that the volume of messages posted during off-market hours can serve as a predictor for fluctuations in both trading volume and stock returns in the following trading day. Similar studies have also found empirical evidence suggesting a correlation between investor sentiment and stock prices (Tumarkin & Whitelaw, 2001; Antweiler & Frank, 2004; Das & Chen, 2007). Fisher and Statman (2002) demonstrated that investor sentiment, as measured by survey data, is positively associated with contemporaneous stock returns. A similar finding was made by (Brown and Cliff, 2004; Schmeling, 2009). Similarly, Baker and Wurgler (2006) constructed a proxy of sentiment index based and found that higher sentiment leads to higher current monthly returns, particularly for stocks that are more difficult to value and arbitrage. In addition to the impact of investor sentiment on stock returns, several studies have also focused on how sentiment influences stock market volatility. For instance, De Long et al., (1990) proposed the "noise trader" model, which suggests that sentiment-driven investors can create additional risk in the market, leading to increased volatility. Lee et al. (2002) found that changes in investor sentiment (American Association of Individual Investors) sentiment index, are positively related to market volatility. Johnston and Nedelescu (2005) found market volatility and market uncertainty due to major disruption in examining the reaction in the market to the 9/11 terrorist attack in the US. Wang et al., (2006) conducted a study on the relationship between investor sentiment and stock market volatility using various sentiment proxies like the American Association for Individual Investors (AAII) and Investor Intelligence (II). They found that sentiment has a significant positive effect on volatility when investors are more pessimistic.

Researchers have explored various factors influencing stock market fluctuations, including fundamental news (Li et al., 2014; Sundaram, 2020), macroeconomic variables (Humpe and Macmillan, 2009; Luís et al., 2021), political events (Bialkowski et al., 2008), natural disasters (Angbazo & Narayanan 1996;

Worthington and Valadkhani, 2004; Shan & Gong 2012; Akter et al., 2023), and even sports outcomes (Edmans et al., 2007). Studies have also found that natural phenomena such as cloud cover (Saunders, 1993), daylight (Kamstra et al., 2000; 2003), sunshine (Hirshleifer & Shumway, 2003), and temperature (Cao & Wei, 2005) can impact stock market sentiment and movement. More recently, the sentiment towards the Covid-19 pandemic has been shown to play a significant role in global market dynamics. Despite the extensive research on investor sentiment and its impact on financial markets, there is a notable lack of comprehensive studies examining the specific influence on extreme shocks like natural disasters on stock market returns and the associated public sentiment.

Significance and scope of the study

The selection of G5 and BRICS countries for this study is strategically significant, offering a comprehensive view of global market dynamics across both developed and emerging economies. This study's multifaceted approach and comprehensive analysis of market behaviour across BRICS and G5 countries make it a valuable contribution to the fields of finance, economics, and behavioural studies. The findings have the potential to influence both academic understanding and practical applications in global financial markets. This study makes significant contributions to finance and market behaviour research. It addresses a crucial gap by examining AMH in BRICS and G5 stock markets, offering insights into market efficiency dynamics in emerging and developed economies. The research introduces an innovative framework for analysing calendar anomalies, enabling more sophisticated cross-market comparisons. By investigating trading strategies based on these anomalies, it bridges theory and practice, providing valuable insights for investors. The study's exploration of disaster sentiment's impact on specific stock returns enhances our understanding of behavioural finance, offering crucial insights for risk management and policymaking during crises. Additionally, it provides substantial empirical support for the AMH, challenging traditional static views of market efficiency. This study will provide important implications for market regulators and policymakers, potentially influencing both academic understanding and practical applications in global financial markets.

Research Design

This section addresses the core components of the research framework. It begins by elucidating the statement of the problem, highlighting the critical issues that necessitate investigation and pinpoints where existing research falls short. The section proceeds to formulate pertinent research questions, these questions serve as the foundation for the study's objectives and hypothesis of the study. Finally, outlines the data and research methodology adopted for the study, the approach and techniques chosen in analysing the data.

Statement of the problem

The longstanding debate between the Efficient Market Hypothesis (EMH) and Behavioural Finance (BF) proponents has been a central issue in financial economics, resulting in conflicting perspectives on market efficiency and investor behaviours. The Adaptive Market Hypothesis (AMH) emerged as an attempt to reconcile these viewpoints, proposing a cyclical model of market efficiency (Lo, 2004; Urquhart & McGroarty, 2016). Recent empirical studies have focused on examining varying degrees of efficiency in both developed and emerging markets through the AMH lens (Ghazani & Araghi, 2014; Noda, 2016). Given the unique characteristics of developing markets, investigating inefficiencies in these economies through the AMH framework is crucial.

Calendar anomalies have also contributed to market inefficiencies, though their persistence remains inconclusive (Dimson & Marsh, 2001; Scwert, 2003). The AMH framework encourages researchers to examine how these calendar-based patterns evolve over time and differ under varying market conditions. Furthermore, while existing literature explores how natural disasters impact stock behaviour, there is a lack of comprehensive analysis on how such events alter sentiment and decision-making processes among market participants. This knowledge gap impedes our understanding of market resilience and efficiency in the face of catastrophic events, leaving unexplored questions about potential anomalies or inefficiencies that may arise in post-disaster periods.

Research gap

Numerous studies have investigated market efficiency using various approaches using parametric or nonparametric test. Despite the widespread application of these tests, a thorough comparative analysis of their relative testing approaches in capturing the time-dependent dynamics of stock returns in BRICS and G5 markets remains unexplored. The contradictory evidence regarding the presence of nonlinear dependencies in stock returns dictates further investigation to reconcile these findings in developed and emerging financial markets. Further, the persistent observation of calendar-based anomalies in stock returns provides inconclusive empirical evidence, warrants further investigation. The existing literature has documented mixed findings regarding the presence and persistence of calendar effects, such as the day-of-the-week and month-of-the-year anomalies, across different markets and time periods. This suggests that these anomalies may exhibit time-varying or market-specific characteristics, which is limited to few markets and remain underexplored using a symmetric and asymmetric GARCH model. Lastly, existing literature explores the impact of natural disasters on stock behaviour in various regions, it lacks a comprehensive analysis of how these events change sentiment and decision-making among market participants. Additionally, there is a lack of detailed examination into disaster-induced mood sentiment on stock returns, leaving unexplored questions about potential anomalies or inefficiencies that may arise in post-disaster periods. To the best of the author's knowledge, no studies have examined the intricate relationship between sentiment-based natural disaster index and stock return, particularly in India.

Research Question

In light of the concerns discussed earlier, it is imperative to answer the following research questions.

1. Are stock price changes dependent or time dependent, do market exhibit time varying dependent or adaptive in stock price movements?

2. To what extent are market anomalies present in developed and developing markets and how does these anomalies evolve overtime?
3. Under which specific market conditions do calendar anomalies produce significant return and how do these conditions vary between developed and developing countries?
4. How trading strategies perform across different markets, and which strategies demonstrate superior risk-adjusted returns in explicit market?
5. How does investor sentiment in stock market respond to natural calamities and does this response differ across different sector?
6. How does investor sentiment in stock market response to natural catastrophic events or does this response differ across different sector?

Objectives of the study

Given the rationale for the research gap and the problem statement, the primary objective of this research is to examine market efficiency and calendar anomalies within the Adaptive Market Hypothesis (AMH) framework in the BRICS and G5 markets, as well as investor sentiment during natural calamities.

1. To examine the time dependence of stock return and adaptive market behaviour in developed (G-5) and developing (BRICS)
2. To identify whether calendar market anomalies are found in developed and developing markets
3. To investigate whether calendar anomalies exhibit the adaptive market pattern in the markets
4. To determine whether trading strategies outperform in various market environments
5. To examine the sentiment behaviour of the stock dynamics during natural calamities

Hypotheses of the study

On the basis of the above objectives, the following hypotheses are formulated to be tested.

H_1: The behaviour of the stock price exhibits time-varying return predictability consistent with the adaptive market hypothesis.

> H_{1a}: The BRICS markets exhibit significant linear time-varying patterns
>
> H_{2a}: The BRICS markets exhibit significant nonlinear time-varying patterns
>
> H_{3a}: The G-5 markets exhibit significant linear time-varying patterns
>
> H_{4a}: The BRICS markets exhibit significant nonlinear time-varying patterns
>
> H_{5a}: The degree of market efficiency changes over time differs in G-5 and BRICS markets

H_2: The stock market exhibits significant calendar anomalies

> H_{2a}: There is a significant day-of-the-week effect in BRICS and G5 market returns
>
> H_{2b}: There is a significant month-of-the-year effect in BRICS and G5 market returns
>
> H_{2c}: There is a significant turn-of-the-month effect in BRICS and G5 market returns

H_3: There is a significant adaptive nature of calendar effects

> H_{3a}: There is significant time varying calendar effects in BRICS financial markets
>
> H_{3b}: There is significant time varying calendar effects in G-5 financial markets
>
> H_{3c}: The adaptive patterns of calendar effects differ between G-5 and BRICS markets

H_4: There is significant profitability in trading strategies based on identified calendar anomalies

H_{4a}: An implied trading strategy (ITS) based on identified calendar anomalies generates higher returns than a simple buy-and-hold (BH) strategy.

H_{4b}: The profitability of the ITS differs between developed and developing markets.

H_5: Investor sentiment during natural calamities has a significant impact on stock market returns

H_{5a}: Natural calamities have a significant negative impact on stock market returns

H_{5b}: Natural disaster sentiment has a significant negative impact on sectors returns

H_{5c}: Hydrological disasters exert a substantial adverse effect on stock returns.

H_{5d}: Stock returns of a firms are significant negative influenced on climate-related disasters and extreme weather events.

H_{5e}: The impact of natural disasters sentiment on stock returns varies across different types of disasters.

Data and Methodology

This study adopts a quantitative research approach, utilizing secondary data on stock returns from the BRICS and G5 markets. The data is obtained from the Trading Economics database and the official websites of the respective countries' stock exchanges, covering a period of 32 years (1 January, 1990 – 31 December, 2022) based on availability of data. The study employs a comprehensive quantitative research approach to achieve its objectives. To investigate the time-dependence and cyclical nature of market behaviour, the analysis utilizes linear dependency tests such as autocorrelation, variance ratio, and unit root tests, as well as a battery of nonlinear tests: the McLeod Li test, Engle LM test, and BDS test. To examine the existence and adaptive nature of calendar anomalies, the study utilizes models from the GARCH family: symmetric (GARCH) and asymmetric (EGARCH) models, within a rolling fixed-window framework of three years. To evaluate the performance of different trading strategies under varying market conditions, the study compares a buy-and-hold (BH) strategy with an implied calendar anomalies trading strategy (ITS). Finally, the Autoregressive Distributed Lag (ARDL) approach is employed to investigate the long-run cointegration, short-run dynamics, and stability of the relationship between the disaster sentiment and sectoral stock returns. Finally, the Granger causality test is applied to examine the potential causal relationships between the investor sentiment proxies and sectoral stock returns.

Limitations of the study

Despite achieving its objectives, this study acknowledges inherent a number of limitations.

1. The sample periods for the observed markets differ in length due to data availability constraints. Two market from emerging markets (MOEX and JALSH), lack sufficient historical data to cover the full intended sample period.
2. A relatively shorter time frame as compared to earlier studies such as Kim et al., (2011) and Urquhart (2013) used a significant long data over a period of 100 years. The study is limited to 32 years' timeframe, longer time frame allows more market events and economic cycle, potential yield more robust result.
3. The choice of fixed three-year rolling window for analysing time-varying efficiency and calendar anomalies. The window size was chosen to balance short-term fluctuations and statistical robustness, the chosen three-year window, may not capture a subtle distinction of market behaviours across different time scales.
4. The reliance on Google sentiment index to gauge investor sentiment, which may not fully represent the entire investor population and could be influenced by factors unrelated to genuine investment intent, potentially affecting the accuracy and generalizability of the findings.

Outline of the Chapter

The current study has been organised and presented in the form of five distinct chapters, as follows:

- Chapter 1: Introduction
- Chapter 2: Theoretical and Literature Framework
- Chapter 3: An Examination on Time Dependent of Stock Return on BRICS and G-5 Countries: A Comparative Analysis
- Chapter 4: The Behaviour of Calendar anomalies and its market condition
- Chapter 5: Investor sentiment towards the market during natural calamities
- Chapter 6: Summary of Findings, Conclusion and Implication

Chapter wise Summary

Chapter 1: Introduction

The first chapter of this thesis demonstrate the background and market analysis for the research, grounding its rationale in the necessity for a more comprehensive assessment of the AMH in emerging markets and developed market. Explores applicability and problem arises in examining time-dependent returns, calendar anomalies, and investor sentiment during natural disasters to address gaps in contemporary financial literature. This chapter outlines the study's justification and emphasizes its primary objectives.

Chapter 2: Theoretical and Literature Framework

Chapter two provides a literature framework covers key areas that lay the foundation for this thesis. The chapter begin with an earlier development of EMH and conferring various stage of development along with forms of EMH, assumptions, and problems in need of its further examination. The chapter then review various stock market anomalies that challenge the classical EMH. These anomalies include the value premium, momentum effect, reversal effect, disposition effect, market bubbles, herding behaviour, size effect, and calendar anomalies. Further, trading rules and technical analysis highlighting the conflict traditional framework in outperform of stock market return in the literature are also presented. The confrontations to the assumptions of EMH by the proponents of BF who believe that investor sentiment have important role to play in shaping the behaviour of financial markets are expounded. The AMH emerges as a model that seeks to reconcile the apparent contradictions between the EMH and BF. The AMH, suggest that markets are context-dependent and subject to evolutionary forces, EMH and BF are co-existing in a rational consistent manner. A literature in support of AMH become a gaining ground, emphasize that markets can differ significantly in terms of their geographical location, operational characteristics, and the size of their respective economies highlighting the need for further examine the AMH across diverse market settings.

Chapter 2: An Examination on Time Dependent of Stock Return on BRICS and G-5 Countries: A Comparative Analysis

Chapter three examines a comparative analysis of time-dependence of stock returns in BRICS and G-5 countries using a comprehensive set of linear and nonlinear tests. The chapter begins with a concise introduction highlighting the limitations of linear models in capturing complex patterns in stock prices. It emphasizes the need to quantify non-linearity in stock market behaviour. Then describes a shift in research approaches, moving from traditional linear modelling techniques to more sophisticated methods that incorporate both linear and nonlinear tests. The chapter then review previous empirical research that utilized these tests and highlights the need for continued research that employs a comprehensive set of tests across different market conditions and time periods. To quantify the empirical results, the study implements linear dependencies test using autocorrelation, variance ratio, and unit root tests. Subsequently, the return series undergoes a non-linear test using a whitening AR and AR-GARCH methods to eliminate linear correlations. The residuals derived from this process are then subjected to a battery of nonlinear tests, including the McLeod Li test, Engle LM test, and BDS test. Following this comprehensive analysis, the observed return behaviours are classified into five predefined categories to examine the behaviour of stock return. The findings predominantly support the AMH, indicating that market efficiency is not a static condition but rather a dynamic process characterized by alternating periods of predictability and unpredictability in stock returns. The linear tests signify G5 stock markets exhibited behaviour consistent with the AMH as compared to BRICS, However, the nonlinear tests consistently uncovered time varying dependencies in stock returns across all markets, suggesting that the AMH provides a more accurate framework for understanding stock market behaviour than the traditional Efficient Market Hypothesis.

Chapter 4: The Behaviour of Calendar anomalies and its market condition

Chapter 4 explores the calendar anomalies and the adaptive calendar effect through an analysis of well-established seasonal patterns in financial markets. The chapter begins with a constraint and flawed efficient theory were challenged with the existence of stock market anomalies were documented with theoretical and empirical evidence. Followed by an extensive literature on Day of the week effect, Month of the year and turn of the month effect. The literature highlights the need for continuous empirical investigation and the consideration using alternative methodologies, time periods, and market contexts to gain a comprehensive understanding these calendar anomalies behaviour overtime. To investigate the existence of calendar anomalies and their time-varying nature, this study employs models from the GARCH family, specifically utilizing both symmetric (GARCH) and asymmetric (EGARCH) specifications. The research examines the adaptive calendar anomalies in the market by implementing GARCH models with a rolling fixed window of three years. This approach allows for the analysis of time varying patterns in the Day-of-the-Week (DOW), Turn-of-the-Month (TOM), and Month-of-the-Year (MOM) effects. The finding show Monday effect was found in BRICS countries and G5 markets exhibited no significant Monday effect. The January effect found to be more prevalent in Developed countries as compared to developing countries and no clear pattern of MOM effect other than January effect was found across the stock markets. Turn of the month effect was found to be significant in BRICS markets and no evidence of TOM was found in G5 markets. An empirical analysis examining time-varying nature of calendar anomalies using rolling three-year subsample, three out of five in BRICS market show adaptive calendar anomalies and Developed markets exhibited adaptive market behaviour, oscillating between efficiency and inefficiency across different sub-periods. Furthermore, this study evaluates the profitability of calendar anomalies by comparing returns from a simple buy-and-hold (BH) strategy with those from an implied calendar anomalies trading strategy (ITS). The result suggests that BH produces higher returns than calendar based ITS strategies in BRICS markets. Potential profitable trading strategies based on Turn of the month and Sell-in -may trading strategy outperform buy-and-hold in G5 Market.

Chapter 5: Investor sentiment towards the market during natural calamities

The fifth chapter focuses on investor sentiment, an increasingly prominent topic in financial research. This area of study has gained significant traction in recent years, challenging traditional finance theories that assume fully rational market participants. The chapter investigates investor sentiment by examining investor behaviour during natural calamities through BSE sectoral index data. The first section provides a comprehensive overview of natural disasters, detailing the various types of catastrophic events that occurred during the study period under examination. Followed by review of the existing literature pertinent to the research topic such as Geophysical effect, Hydrological effect and meteorological effect as well as influenced by investor sentiment towards climate-related disasters and extreme weather events are examined. The third section outlines the methodological approach employed throughout this chapter, with particular emphasis on the complex process of constructing and quantifying investor sentiment—a critical component of the analysis. The empirical finding shows natural calamities had a mixed effect on different sectors. While some sectors like FMCG, Consumer durables, IT, Oil & Gas, Metal, and Realty showed negative impacts, others like Teck and Energy saw positive effects. The overall market index (Sensex) showed a significant positive effect. Further, Climatological disasters (e.g., cold waves, avalanches, glacier outbursts, heatwaves) generally had positive effects on sectoral returns. Negative effects were observed during cyclones, earthquakes, floods, and storms. The second section of the empirical analysis examine relationship of investors sentiment and sectoral stock return show disaster sentiment significantly influenced sectors like capital goods, energy, FMCG, financial services, industrial, and power in the long run. In the short run, disaster sentiment had a more pronounced impact on sectoral index, with significant negative relationships observed in most sectors except a positive relationship in the IT sector. Overall, the study found that disaster sentiment is a significant driver of stock returns, complementing other sentiment measures like Market Mood Index and Volatility Index.

Key Findings

Table 6.1: Key findings

Research Objective	Findings
To examine the time dependence of stock return and adaptive market behaviour of return in developed (G-5) and developing (BRICS)	**Linear Autocorrelation test:** Except MOEX, the BRICS and G5 markets experience time varying dependence of stock return. **Linear Variance ratio test**: The BRICS market show an inconclusive result on whether the market is time-dependence. However, the G5 markets show a time varying return dependence **Nonlinear battery test:** All markets under study provided evidence of significant nonlinear dependence in stock returns. **Nonlinear AR-GARCH BDS test**: The findings indicate that both BRICS and G5 markets exhibit behaviour that aligns with the Adaptive Market Hypothesis (AMH)
To examine existence of calendar market anomalies in developed and developing markets	**DOW effect**: The DOW effect was found to be more relevant in developing markets compared to developed markets. **MOY effect**: The MOY effect is widespread in developed market as compared to emerging markets. **TOM effect:** Turn of the month effect was found to be significant in developing and developed markets
To investigate whether calendar anomalies exhibit the potential adaptive market pattern in the markets	Emerging markets like JALSH, MOEX, and SSE showed significant widespread adaptive market anomalies with excess returns, developed markets experienced oscillating between efficiency and inefficiency displayed significant form of episodic anomalies.
To identify which trading strategies, outperform under different market condition	The Buy and Hold trading strategy produce higher returns than ITS strategies in BRICS markets. The SIM and BH strategy outperformed in the G5 market.

To examine the sentiment behaviour of investors in stock market during natural calamities	The result suggests that there is a significant impact on market reaction due to natural calamities. The disaster sentiment proxy exhibited a significant influence on various sectors like capital goods, energy, FMCG, financial services, industrial, and power. A significant negative relationship was observed between DSI and sectoral returns across auto, capital goods, FMCG, financial services, industrial, power, metals, oil and gas, and realty sectors The Disaster Sentiment Index (DSI) exhibited Granger causality for sectors like capital goods, industrial, power, telecommunication, realty, and the overall market index. Overall, this implies sentiment behaviour of investors has a predictive power over returns.

Concluding remarks

In conclusion, this comprehensive study provides compelling evidence in supporting the Adaptive Market Hypothesis (AMH) in both developed and emerging markets. The research, spanning the BRICS and G5 countries from 1990 to 2022, demonstrates that market efficiency is not a static condition but a dynamic process characterised by alternating periods of predictability and unpredictability in stock returns. The findings reveal that the behaviours of stock returns in G5 markets are more consistent with AMH in linear tests, and nonlinear analyses uncovered time-varying dependencies across all markets, suggesting that AMH offers a more accurate framework for understanding stock market behaviour than the traditional Efficient Market Hypothesis. The investigation of calendar anomalies further reinforces this adaptive nature, with emerging markets showing more pronounced day-of-the-week effects and developed markets displaying stronger month-of-the-year patterns. Notably, the study finds that simple buy-and-hold strategies often outperform calendar-based trading strategies in BRICS markets, whereas certain anomaly-based strategies are profitable in G5 markets. The examination of investor sentiment in the Indian stock market during natural disasters adds another layer to our understanding, revealing that disaster sentiment significantly influences various sectors and has predictive power over returns. These findings collectively underscore the complex and evolving nature of financial markets and the importance of considering both rational and behavioural factors in investment decisions and policymaking. The study contributes valuable insights to the ongoing debate between traditional finance theories and behavioural finance, suggesting that a more significance adaptive approach is necessary for understanding and navigating modern financial markets.

Novelty of research and contribution to knowledge

This study contributes to the literature on efficient markets, adaptive markets, calendar anomalies, and investor sentiment in several key ways.

- This study investigates the validity of AMH within BRICS and G5 stock markets, an area underexplored in existing literature. Efficiency as a time-varying parameter, as proposed by AMH, was assessed using linear and nonlinear tests. The findings empirically support AMH, affirming its view of market efficiency as a dynamic process influenced by evolving conditions.
- This study broadened its analytical scope by integrating various statistical models, including advanced methods like GARCH, EGARCH, ARDL, and causality analysis. Utilizing this extensive array of techniques aimed to mitigate potential biases and improve the reliability of findings relative to earlier research in the field.
- The thesis also contributes to the literature on calendar anomalies under the AMH. The empirical findings highlight the dynamic nature of calendar anomalies, showing that markets oscillate between periods of efficiency and inefficiency. From a practical standpoint, the adaptive nature of calendar effects can be attributed to behavioural biases, market frictions, geopolitical dynamics, and changing market conditions that the static approach to EMH fails to adequately explain.
- This study makes significant contributions to our understanding of calendar anomalies and their potential to generate excess returns through trading strategies.

- Finally, this thesis provides empirical evidence to support the validity of investor sentiment and stock market dynamics, particularly during extreme natural calamities.

Implication of the study

The outcome of this study suggests possible practical implications for various stakeholders in financial markets.

For Institutional investment and retail investors

1. The study documented that the market undergoes different periods of return efficiency and inefficiency. Thus, market participants should be treated or viewed in different ways. Techniques such as market timing, sectoral rotation, and security selection should be used by institutional or retail investors in diverse market environments subject to specialist concepts.
2. The findings also document that time-varying return predictability, suggesting arbitrage opportunities, arise in financial markets from time to time, and investors must be aware of these possibilities to earn abnormal returns.

3. Empirical evidence suggests that market performance can vary significantly across different environments. This heterogeneity in market behaviour underscores the importance of a market-specific analysis for retail investors. In order to mitigating risks associated with changing market conditions, it would be prudent for investors to adopt adaptive investment strategies that can adapt to fluctuations in market efficiency and the evolution of calendar anomalies.

4. The result of the finding suggests that disaster sentiment as a significant driver of stock market returns. In addition to the market mood index and volatile index, it is prudent to consider the Google search volume index as a proxy indicator of market sentiment.

5. The empirical evidence suggests that a buy-and-hold strategy has demonstrated superior performance across a majority of market conditions. This study reveals that reliance on technical analysis and specific trading strategies for predicting return movements may prove ineffective in yielding the desired outcomes. A hybrid approach combining the long-term stability of a buy-and-hold strategy with sentiment-informed adjustments may be optimal.
6. Institutional investor managers should adopt a balanced approach that emphasises both survival strategies and profit maximisation when conducting targeted market analyses. By implementing this approach, institutional managers can better navigate market complexities, mitigate risks, and capitalise on market inefficiencies, while ensuring their institution's long-term viability.

For Policy Marker

1. Policymakers should integrate investor sentiment analysis into regulatory frameworks by employing a dual approach to address both rational and emotional market behaviours. This includes the implementation of a sentiment monitoring system that utilises advanced analytics to track real-time investor mood shifts and design adaptive regulatory mechanisms that respond to significant changes in sentiment.
2. The dynamic nature of market efficiency suggested by AMH requires more flexibility with tightened information disclosure and timeliness information, along with taking policy measures to control the volume flow of institutional investors that reduce the wavelength of price movement. to mitigate the excessive price volatility.
3. The significance of market inefficiency in eliciting trader strategies and its dynamic nature in shaping regulatory frameworks provides valuable insights for policymakers, enabling them to adapt to financial innovations and foster economic development through the implementation of evidence-based policies derived from analyses of market efficiency evolution.
4. Policymakers should integrate sentiment analysis into their decision-making processes to develop more effective investor education programs that focus

on identifying and addressing common predispositions that impact market dynamics, thereby empowering investors with the knowledge and skills necessary to navigate complex financial environments.

5. Policymakers should adopt a comprehensive strategy to regulate extreme market activities. This should include stringent in reporting requirements that enabling regulators to quickly identify potential market distortions, enhancements to existing circuit breakers and trading halts during periods of market turbulence, and incentives or mandates for using alternative trading systems, like batch auctions, to reduce market distortions and enhance stability.

Limitations of the study

Despite achieving its objectives, this study acknowledges inherent a number of limitations.

1. The sample periods for the observed markets differ in length because of data availability constraints. Two market from emerging markets (MOEX and JALSH), lack sufficient historical data to cover the intended sample period.
2. The study's focus on a limited number of emerging markets, excluding key emerging market such as Thai, Vietnam, and Hong Kong stock markets, may lead to potential biases and an incomplete representation of the broader emerging market landscape.
3. A relatively shorter time frame compared to earlier studies, such as those by Kim et al. (2011) and Urquhart (2013), used significantly longer data over a period of 100 years. The study is limited to 32 years' timeframe, a longer timeframe allows more market events and economic cycles, and the potential yields more robust results.
4. A fixed three-year rolling window is used to analyse time-varying efficiency and calendar anomalies. The window size was chosen to balance short-term fluctuations and statistical robustness, the chosen three-year window, may not capture a subtle distinction of market behaviours across different time scales.

5. The reliance on the Google sentiment index to gauge investor sentiment may not fully represent the entire investor population and could be influenced by factors unrelated to genuine investment intent, potentially affecting the accuracy and generalisability of the findings.

Suggestion for further Studies

Future research on AMH holds significant potential due to its recent emergence and growing relevance in finance. Future studies could develop a quantitative framework to measure and predict market adaptability across various asset classes and examine context-specific market behaviours. Longitudinal studies can be tested across different markets over extended timeframes and analyse market efficiency dynamics in response to economic, technological, and social changes. Evaluate whether advanced machine learning techniques can predict market adaptations, as proposed by AMH, by incorporating algorithms to analyse large datasets on market behaviours, investor sentiment, and macroeconomic indicators. Additionally, further study can investigate adaptive investment strategies that dynamically adjust to market conditions using real-time data and AI-driven decision-making. This could validate the AMH and offer practical applications for investors and policymakers in complex global financial markets. Furthermore, it is recommended that advanced sentiment analysis be incorporated into financial modelling, the impact of exogenous events on market adaptation be assessed, and interdisciplinary approaches be explored. Moreover, the influence of emerging financial technologies and the necessity for long-term studies on market evolution should be addressed with broadly and generalizable.

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