Calendar Anomalies in Equity and Foreign Exchange Markets: An Empirical Study

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By

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DECLARATION

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

Place: Taleigao Plateau.

Date :   -   -2025   Mr. Tuyekar Suraj Prakash

CERTIFICATE

I hereby certify that the above Declaration of the candidate, Mr. Tuyekar Suraj Prakash is true and the work was carried out under my supervision.

Prof. Y.V. Reddy

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Acknowledgment

The journey toward completing this thesis has been one of deep learning, perseverance, and personal transformation. As I stand at its culmination, I extend my heartfelt gratitude to the divine guiding force and to all those whose encouragement made this accomplishment possible.

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Dedicated with deep gratitude to

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Abbreviations

DOW:	Day-of-the-Week
TOM:	Turn-of-the-Month
TOY:	Turn-of-the-Year
HM:	Half-Month
MOY:	Month-of-the-Year
HY:	Half-Year
WOM:	Week-of-the-Month
CC:	Close to Close
CO:	Close to Open
OC:	Open to Close
TGARCH:	Threshold Generalized Autoregressive Conditional Heteroskedasticity
USD:	United States Dollar
EUR:	Euro
GBP:	Great British Pound
JYP:	Japanese Yen

Chapter 1

Introduction

The notion of efficient capital markets posits that asset prices fully reflect all available information, making it difficult to consistently generate returns above the market average through either technical or fundamental analysis. It implies that in an efficient market, prices adjust very rapidly to the new information and only risk-taking can yield higher returns (Fama 1991; Malkiel 1991; Malkiel and Fama, 1970). In contrast, calendar anomalies describe recurring trends in asset returns linked to particular times of the year, such as certain days or months. If in any market, there is possibility of generating abnormal returns due to particular patterns formation in returns than it is termed as market anomaly. The anomalies may appear, disappear and reappear over a period of time. Some anomalies appear once, whereas some appear continuously. Seasonality is a systematic pattern in the time series. This study aims to investigate whether emerging markets like Indian stock market and others does have the seasonal patterns that have been noticed in other countries. Some studies have found that efficient market hypothesis holds true and there is no scope for generating abnormal returns for the investor. However, there are different types of market anomalies that are studied by the researchers. In the stock market, the anomalies provide investors the opportunity to make short-term profitable strategies, as the anomalies do not exist over a longer period. Anomalies tend to disappear, as the investor gets aware about the same. The conviction of the investor that, the market is not efficient all the time and observation of the seasonal patterns in the returns help them to formulate their investment strategies. Thus, it is possible for the investor to beat the market and generate abnormal returns by exploiting the market anomalies. However, overall returns in financial markets have two different components trading day returns and non-trading day returns. Trading day returns represent the price movements that occur during the normal operating hours of the financial market when trading activity is active and accessible to all market participants. Non-trading day returns capture the price movements that happen when the market is not operational and trading is unavailable to investors. Analysing both trading day returns and non-trading day returns separately can provide valuable insights into the behaviour and anomalies of financial markets. These insights can be valuable for making informed investment decisions, developing trading strategies, and enhancing risk management practices. The most common calendar effect explored by different researchers in different countries is Day-of-the-week effect that refers to the situation where there is a difference in returns of day of the week, that is, investor can possibly make abnormal returns by trading on specific day of the week. Some studies (Alagidede, 2008; Poshakwale, 1996; Sudarvel and Velmurugan, 2015) have proven that Monday returns are lower than Friday returns, as the investors' optimistic behaviour on weekend tends to push the prices of the stock. Another most tested anomaly is Turn-of-the-Month (TOM) effect refers to the pattern in which stock prices generally show higher returns on the last trading day of a month and during the first few trading days of the following month. Similarly, the Turn-of-the-Year (TOY) effect, often called the January anomaly, describes the tendency for stocks to exhibit relatively stronger performance in the first two to three weeks of January. Investor 'happy mood' and positive attitude during year end and start of New Year tends to hike the prices of the stocks.

1.1 Theoretical Background

Financial markets are traditionally grounded in the Efficient Market Hypothesis (EMH) proposed by Fama (1970), which asserts that asset prices fully and instantaneously reflect all available information. According to EMH, investors cannot consistently achieve abnormal returns through timing strategies or exploiting predictable price patterns, as price movements follow a random walk (Samuelson, 1965). However, extensive empirical evidence over the past several decades has challenged this theoretical premise by documenting persistent deviations from randomness. These deviations commonly referred to as market anomalies indicate that investor behaviour, structural market frictions, and institutional characteristics may generate predictable patterns in returns.

Among various types of anomalies, calendar anomalies have attracted significant academic and practitioner interest. Calendar anomalies represent systematic variations in returns associated with specific time periods, such as days of the week, months of the year, or certain transitional intervals like the turn of the month or year. Classic anomalies such as the Day-of-the-Week effect (Cross, 1973; French, 1980), January effect (Rozeff & Kinney, 1976), Turn-of-the-Month effect (Rogalski, 1984), and Semi-Monthly effect (Ariel, 1987) provide strong evidence that market returns are not purely random. These effects are often attributed to institutional practices, behavioural biases, liquidity shifts, tax-loss selling, settlement cycles, window dressing, and periodic investor activity.

Over time, the focus of calendar anomaly research has expanded from broad market indices to sectoral behaviour, firm-size variations, and cross-country comparisons, especially within emerging markets where structural inefficiencies and investor sentiment may be more pronounced. Sector-specific anomalies have been connected to differences in information flow, risk exposure, and business cycles. Size-based examinations highlight that small-cap, mid-cap, and large-cap indices may respond differently to seasonal patterns due to variations in liquidity, market coverage, and institutional participation. Meanwhile, international evidence suggests that emerging markets characterized by higher volatility, evolving regulatory frameworks, and heterogeneous investor bases often display stronger or more persistent anomalies than developed markets.

In addition to return patterns, modern financial theory emphasizes the importance of volatility dynamics, acknowledging that financial time series exhibit heteroskedasticity, volatility clustering, and asymmetric responses to market shocks. This foundation is supported by Engle's (1982) ARCH model and Bollerslev's (1986) GARCH extension. The presence of the leverage effect, where negative shocks lead to disproportionately larger increases in volatility compared to positive shocks (Zakoian, 1994), further deepens the theoretical relevance of studying anomalies alongside volatility behaviour. Models such as TGARCH capture these asymmetric adjustments and offer insights into how return patterns interact with conditional volatility, an essential consideration for markets where investor reactions vary with news intensity.

Calendar anomalies have also been explored in the foreign exchange market, although to a much lesser extent compared to equity markets. Foreign exchange markets, being highly liquid and globally integrated, are theoretically expected to be efficient. Yet studies acknowledge the presence of DOW effects, monthly patterns, and time-zone-driven behavioural biases even in currency markets. Investigating anomalies across major exchange rates (USD, EUR, GBP, JPY) provides a broader understanding of market microstructure, trader behaviour, and global capital flow patterns.

Overall, the theoretical foundation of this study lies at the intersection of market efficiency, behavioural finance, and time-varying volatility models. By examining calendar anomalies across major stock indices, sectoral indices, size-based indices, emerging market returns, and foreign exchange rates, the study contributes to a deeper theoretical understanding of return predictability, behavioural dynamics, and volatility interactions in modern financial markets. This comprehensive framework provides a rich theoretical basis for evaluating whether financial markets particularly in emerging contexts adhere to efficiency or systematically diverge due to seasonal and behavioural influences.

1.2 Literature Review

Cornell (1985) used approach of close to close, close to open and open to close in order to study the day of the week effect. It was revealed that the weekly pattern exist primarily due to the unusual behaviour of cash prices during non-trading hours. Kato (1990) noticed that returns are low on Tuesday and high on Wednesday. Most of the positive returns were witnessed during the non-trading period. Further, Rastogi, Bang, and Chaturvedula (2011) used similar approach of decomposing the returns into trading and non-trading returns to examine the day of the week effect by taking into consideration volatility during trading and non-trading hours. However, they did not provide any evidence on presence of any other calendar anomalies and the sector wise evidence. Mitra (2016) investigated the presence of the day of the week in NSE Nifty and BSE Sensex. They concluded that there is no existence of Day-of-the-Week effect on the return of Sensex and Nifty indexes. However, they found volatility to be statistically significant on Tuesday return. Raj and Kumari (2006) tested various calendar anomalies, including weekday, weekend, January, and April effects, by employing multiple regression with dummy variables. They found Indian stock market does not display typical seasonal anomalies like the Monday and January effects. Elango & Al Macki (2008) using data from three major NSE indices covering 1999-2007, assessed the existence of the weekend effect in India's emerging equity market. They employed K-W test, Regression & Wilcoxon Mann-Whitney pair-wise test to study weekend effect. Their analysis revealed mixed evidence, with negative Monday returns for two indices and significant day-of-the-week differences. Dummy variable regression further confirmed inefficiency in the NSE S&P Nifty, while Wednesdays consistently showed the highest returns alongside elevated volatility. Jassal and Dhiman (2017) studied stocks of eleven different sectors by employing GARCH model. Their study revealed the presence of a Friday effect in both the banking and private sector banking indices. Additionally, Wednesday returns were observed to be positive and significant for the FMCG and pharmaceutical sectors, while Monday and Tuesday returns showed positive and significant effects for the FMCG and private sector banking indices.

According to Demirer and Baha Karan (2002) positive return on the first trading day signals the overall performance trend for the remainder of the week. They found that despite return efficiency, the market remained inefficient in predicting volatility and accurately reflecting investor sentiment. Different techniques has been employed by the researchers to investigate the presence of calendar anomalies. Patel and Patel (2011) tested the days of the week effect using parametric and nonparametric tests. Rahman (2009) employed the GARCH (1, 1) model and findings were in support of presence of significant day of the week effect in Dhaka Stock Exchange (DSE). Verma (2016) study applied dummy variable regression with ANOVA to examine the Day of the Week effect. But they found that there is no existence of day of week effect in BSE Bankex. Kumar and Jawa (2017), using a similar methodology, examined the presence of calendar anomalies in the Indian stock market. Their findings indicated significant calendar effects, particularly the presence of a Wednesday effect and a December effect. Sudarvel, Dhanu, and Velmurugan (2017) confirmed the existence of the Day-of-the-Week, Semi-Month, and Turn-of-the-Month effects using OLS regression and paired t-tests. They suggested that the Indian market is inefficient, that allow investors to potentially enhance returns through market timing strategies. Ignatius (1992) explored the seasonality in stock returns on the BSE and the NYSE by employing regression and Kruskal-Wallis test. The BSE exhibited seasonal effects, with the highest average returns in December and during the fourth week. The author suggested that the BSE and NYSE remain segmented rather than fully integrated. Nishat and Mustafa (2002) suggested Karachi Stock Market is efficient and no patterns in the daily returns. Srinivasan and Kalaivani (2014) employed ARCH family models models to examine the existence of daily anomalies. Their study results indicated the existence of day-of-the-week effects on stock returns and volatility of the Indian stock markets. Vodwal (2017) conducted a study of seven East Asian stock markets, employed GARCH-M(1,1), GJR-GARCH-M(1,1), and E-GARCH-M(1,1) models to investigate calendar anomalies such as the Day-of-the-Week, TOM, Holiday, and January effects. The results indicated no significant presence of these anomalies, highlighting a strong degree of operational efficiency in the examined markets. Munusamy (2018) using OLS, GARCH(1,1), and GJR-GARCH(1,1) models confirmed a significant Ramadan effect on both returns and volatility in India’s Shariah indices. The study revealed that returns were significantly higher during Ramadan as compared to non-Ramadan periods, with Wednesdays exhibiting notably stronger gains than other weekdays. Hasan et al. (2022) evaluated seven calendar anomalies in both conventional and Islamic stock indices of Bangladesh using

GARCH models over almost a decade period. They confirmed the existence of these anomalies, except for the Ramadan effect. Sharma (2011) suggested that there is no existence of calendar anomalies in Indian stock market. However, investor must keep in mind that these anomalies can persist or disappear in a certain course of time (Vandana Khanna, 2016). Several other studies conducted in the Indian context have also examined the presence of calendar anomalies (Poshakwale, 1996; Sudarvel and Velmurugan, 2015; Lodha and Soral, 2015; Archana, 2014; Sri Ram, and Ramesh, 2014).

The earlier studies in Middle Eastern and Asian emerging stock markets consistently found significant calendar anomalies, challenging the efficient market hypothesis and suggesting exploitable inefficiencies for investors (Mishra, 2017; Rasool et al., 2023; Shehadeh & Zheng, 2023). Agarwal and Tandon (1994) examined five seasonal patterns in stock markets of eighteen countries. They found daily seasonal effect in nearly all the countries but weekend effect in only nine countries. Their study also revealed that last trading day of the month has large returns and low variance in most of the countries. According to Georgantopoulos, Kenourgios, and Tsamis (2011) anomalies such as the DOW and turn of the month effects are more pronounced in mature markets, while in less developed markets, these effects are mostly limited to volatility, possibly due to lower liquidity and market maturity. In 2025, Gadhavi suggested differing levels of market efficiency across BRICS countries in the context of the currency market. The author for the purpose of analyses combined dummy variable-based OLS regression with the GARCH(1,1). The study found the Indian Rupee and Chinese Yuan exhibited signs of inefficiency, suggesting opportunities for profitable trading strategies, whereas the other currencies demonstrated efficiency with no consistent exploitable patterns. Analyses before and after the COVID-19 pandemic in Asian markets show that calendar anomalies persist but shift in timing and magnitude, with volatility and returns varying across months and countries (Rasool et al., 2023). In Islamic frontier markets, calendar anomalies are generally weak, with only minor effects detected, supporting weak-form market efficiency (Aslam et al., 2022). The Nepalese stock market, for example, exhibits a persistent day-of-the-week effect but little evidence for other anomalies, indicating partial inefficiency (K. C. & Joshi, 2005). Emerging markets, due to their developing institutional frameworks and retail investor dominance, have frequently demonstrated such anomalies. Moreover, these markets exhibit volatility asymmetries, wherein negative news led to disproportionately larger volatility increases. Common approaches include regression analysis with dummy variables to test for effects like day-of-the-week, month-of-the-year, or holiday anomalies, as well as more advanced models such as GARCH or AR-GARCH to account for volatility and time-varying behaviour in returns and anomalies (Aleknevičienė, Klasauskaitė, & Aleknevičiūtė, 2021; Hasan et al., 2022; Patel, 2024; Shehadeh & Zheng, 2023; Villarreal-Samaniego, 2024; Wuthisatian, 2022). Ajayi, Mehdian, and Perry (2004) conducted an empirical investigation of the day of the week effect considering eleven Eastern European emerging markets. Their study found absence of consistent and statistically significant daily return anomalies across the examined stock markets. Nwachukwu and Shitta (2015) assessed weak-form market efficiency across 24 emerging and nine industrial stock indices worldwide. Their findings revealed that reformed emerging markets provided superior risk-adjusted returns and greater return predictability compared to industrial markets. They also found that TOY effect was more prevalent in emerging economies, while evidence supporting the tax-loss selling hypothesis remained limited across both market groups. Aggarwal and Jha (2023) using ARCH family models and found that ARCH and GARCH effects exists in monthly returns and confirmed returns exhibit a significant leverage effect. Tuyekar, Padyala, and Ramesh (2023) investigated the existence of calendar anomalies in trading and non-trading day returns in Indian stock market using GARCH(1,1) model. They suggested buying on Tuesday and sell on Wednesday. Omran and Farrar (2006) tested the validity of the random walk hypothesis and found the existence of calendar effects in the stock returns in five major emerging markets of the Middle East. Singh, Bhattacharjee, and Kumar (2020) employed Ordinary Least Squares (OLS) regression to investigate the presence of the TOM effect and assess the efficiency of emerging stock markets. Their study results indicated that during the crisis period, the anomaly vanished in Brazil and India but remained significant in China. However, the calendar anomaly re-emerged across all countries in the post crises period. Vasileiou (2021) suggested investment strategies for both local and international investors based on the TOM effect that can outperform the broader market, especially for investors trading in USD. Even there is attempt to test Day of the week effect anomaly in cryptocurrency market (Verma, Sharma, and Sam, 2023). The study by Guidi, Gupta, and Maheshwari (2011) tested weak-form efficiency and daily anomalies in Central and Eastern European equity markets using basic and GARCH-M models. Their study suggested that some markets are inefficient, allowing informed investors to generate abnormal returns. Lobão (2019) noticed a strong pre-holiday effects and other seasonal anomalies in ADRs, with patterns more pronounced in those from emerging markets-based ADRs. Al-Khazali (2008) examined the impact of thin trading on calendar anomaly in the emerging equity markets of the UAE and noticed that the anomaly vanishes after adjusting for thin and infrequent trading. Villarreal-Samaniego (2024) explored the time-varying behavior of the Weekend, TOM, January, and Halloween effects across eight foreign exchange rates relative to the U.S. dollar. The study confirmed that these calendar anomalies display a dynamic and evolving presence, especially among emerging market currencies. Compton, A. Kunkel, and Kuhlemeyer (2013) investigated calendar anomalies in Russia's stock and bond markets during the early 2000s. Their findings reveal a persistent monthly pattern and significant weekday seasonality in the Russian bond market, though without the typical January or Monday effects. Additionally, strong TOM effects were observed in Russian stock and bond markets.

Some studies (Kumar, 2015; Kumar & Pathak, 2016) investigated calendar anomalies in India's currency market for the INR against the USD, EUR, GBP, and JPY between January 1999 and April 2014 using OLS regression. Their results indicated no consistent opportunity for excess returns, suggesting increased efficiency in the Indian currency market over time. Patel (2016) tested the presence of the January effect in U.S. and various international stock markets employing OLS regression analysis. The findings indicated that the January effect has largely diminished in global stock returns. Other markets, such as the Thai stock market have also confirmed daily and montly anomalies (Watanapalachaikul and Islam, 2006). Ariss, Rezvanian, and Mehdian (2011) argued that the distinctive characteristics of GCC stock markets could constrain the relevance of calendar anomalies commonly observed in other regions. Nevertheless, their findings indicated that, despite these unique market features, calendar anomalies similar to those in international markets do exist within GCC markets. From the literature reviewed it is identified that the evidence on existence of such anomalies is mixed.

1.3 Research Gap

Literature review supports that the markets are not efficient all time and there is a lot to understand why it deviates from EMH and the possible answer to this is anomalies. Past studies have studied the presence of anomalies in developed markets and the results are mix depending on the period of the studies. However, the presence of anomalies in emerging market has always been a topic of interest for the researchers. Nevertheless, a conclusive evidence on which is missing in the literature. Testing the presence of anomalies in other markets other than stock market is also an interesting area that is not extensively studied. Studies like (Cornell, 1985; Kato, 1990; Mitra, 2016; Agarwal and Tandon, 1994; Jassal and Dhiman, 2017) focused more on the day of the effect anomaly. Other studies (Rahman, 2009; Srinivasan and Kalaivani, 2014) that considered volatility but did not considered trading and non-trading day returns. Therefore, one potential research gap from the existing literature that could be explored is the investigation of how calendar anomalies in trading and non-trading day returns differ across different sectors in the Indian stock market and will provide sector specific market behaviour. Further, analysing these anomalies in size-based indices can provide insights into behavioural biases, market efficiency, and risk-return dynamics across firm sizes. This study not only concentrate on Day of the week effect but also the other calendar anomalies such as Week-of-the-month, Half-monthly, Month of the year, Half-yearly, Turn-of-the-year and Turn-of-the-month effect. Another reason why we examine these anomalies in the Indian stock market is that, India being the emerging market it becomes ideal market to test the hypothesis for these anomalies.

Although extensive research has been conducted globally on calendar anomalies and volatility asymmetries, the findings remain inconsistent, market-specific, and limited in scope, especially for emerging countries. Moreover, there is a lack of unified research employing a consistent methodological framework specifically, Dummy Variable Regression and TGARCH model to systematically assess both return anomalies and volatility asymmetries across multiple emerging markets over a long and recent sample period. Existing studies often focus on isolated markets or anomalies without offering a comprehensive, cross-country perspective. Additionally, limited attention has been given to these anomalies during recent market phases, including the post-global financial crisis and Covid-19 periods. Therefore, this study addresses this gap by employing both dummy variable regression and TGARCH model to investigate the existence and persistence of seven calendar anomalies and leverage effects across select seven emerging markets. Further study examines anomalies in foreign exchange market over an extended and updated period, offering valuable insights for investors, policymakers, and market efficiency theory.

1.4 Scope of the study

The study covers an extensive time horizon across multiple financial segments to provide a comprehensive assessment of calendar anomalies. The analysis is conducted on the Nifty50 index over a 29 year period from 1st January 1996 to 31st December 2024, along with fourteen sectoral indices whose sample periods vary based on data availability. To understand how firm size influences anomaly patterns, the study further includes daily returns of Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250 indices over a 14-year period from 1st January 2011 to 31st December 2024. The scope also extends to a global perspective by examining seven emerging market indices, covering 1st January 2001 to 31st December 2024, while also incorporating volatility dynamics using the TGARCH (1,1) framework. Additionally, the study investigates the foreign exchange market by analysing daily exchange rates of USD, EUR, GBP, and JPY over 1st January 2001 to 31st December 2024, with the total period segmented into four sub-phases: Pre-Crisis (2001-2006), Post-Crisis Recovery (2009-2014), Reform & Stabilization (2015-2019), and Post-Pandemic (2021-2024), with years of extreme disruptions (2007-2008 and 2020) excluded. Through this multi-layered structure, the study encompasses sectoral, size-based, cross-country, and currency market perspectives, providing a broad and comparative understanding of calendar anomalies and their implications for investment and policy decisions.

1.5 Need of the study

Although a considerable body of research has examined market anomalies, including various forms of calendar effects, the findings remain largely inconclusive. Some studies support the Efficient Market Hypothesis (EMH), while others confirm the presence of predictable return patterns, indicating market inefficiencies. Moreover, most existing studies do not simultaneously account for factors such as sectoral differences, market volatility, and firm size (market capitalisation), which may influence the manifestation and strength of calendar anomalies. Understanding how calendar effects vary across sectors and market-cap segments is important for investors who operate under diverse risk-return preferences and investment strategies. Additionally, emerging markets often display unique behavioral and structural characteristics, leading to return patterns that differ from those observed in developed markets. Therefore, a comparative analysis across select emerging economies can provide meaningful insights into cross-market variations in anomalies. Further, the literature focusing specifically on calendar anomalies in foreign exchange markets is limited. Considering the increasing integration of global financial markets, examining anomalies in both equity and foreign exchange markets becomes relevant for investors, policymakers, and portfolio managers. Hence, this study aims to address these gaps by investigating the existence and nature of calendar anomalies across selected emerging markets, sectors, and market-cap categories, thereby contributing to a more comprehensive understanding of market dynamics and aiding investors in making informed decisions.

1.6 Research Questions

The present study formulates the following research questions in light of the research gaps identified in the existing literature.

1. Do trading and non-trading day returns in sectoral indices of the Indian stock market exhibit calendar anomalies such as Day-of-the-week, Week-of-the-month, Half-monthly, Month-of-the-year, Half-yearly, Turn-of-the-year and Turn-of-the-month effect?
2. How do size-based indices (large-cap, mid-cap, small-cap) in the Indian stock market differ in their susceptibility to calendar anomalies?
3. Do emerging market stock indices reflect similar or divergent patterns of calendar anomalies compared to the Indian stock market, and how does the volatility leverage effect interact with these anomalies?
4. Are calendar anomalies present in select foreign exchange returns?

1.7 Objectives of the Study

1. To examine whether calendar anomalies exist in trading day and non-trading day returns across sectoral indices of the Indian stock market.
2. To investigate the presence of calendar anomalies in size-based indices (large-cap, mid-cap, and small-cap) of the Indian stock market.
3. To investigate the existence of calendar anomalies and the volatility leverage effect in select emerging market indices.
4. To analyse the presence of calendar anomalies in select foreign exchange returns.

1.8 Research Methodology

The study uses daily time-series data to examine the presence of multiple calendar anomalies across sectoral indices, size-based indices, emerging market indices, and major foreign exchange rates. Daily log returns are computed from opening and closing prices, and the stationarity of each return series is verified using the Augmented Dickey–Fuller (ADF) test. To test for anomalies such as Day-of-the-Week, Week-of-the-Month, Month-of-the-Year, Turn-of-the-Month, Turn-of-the-Year, Half-Month, and Half-Year effects, the study applies dummy-variable regression models, where each calendar phase is represented using binary indicators. The analysis covers long-term datasets: Nifty50 from 1996–2024, 14 NSE sectoral indices with varying sample availability, size-based indices (Nifty 100, Midcap 150, Smallcap 250) from 2011-2024, emerging market indices (Brazil, China, Indonesia, Mexico, India, Russia, Turkey) from 2001–2024, and major currencies (USD, EUR, GBP, JPY) from 2001-2024. For emerging markets, volatility behaviour is additionally examined through ARCH-LM tests and TGARCH(1,1) models to capture conditional heteroskedasticity and leverage effects. For foreign exchange markets, the study also analyses the persistence of anomalies across four sub-periods representing distinct economic regimes.

1.9 Significance of the study

This study holds significant relevance for investors, portfolio managers, policymakers, and researchers by offering a comprehensive and multi-dimensional understanding of calendar anomalies in financial markets. By examining anomalies across sectors, market-cap segments, emerging market indices, and foreign exchange rates over extended time periods, the study provides deeper insight into whether return patterns are systematic or merely random. The distinction between trading-day and non-trading-day returns adds further clarity to how market activity and investor behaviour may differ across time segments. Identifying persistent anomalies can help investors in timing strategies, risk management, and portfolio allocation, while the analysis of volatility dynamics through models like TGARCH (1,1) contributes to a better understanding of market sensitivity to information. For policymakers and regulators, the findings can serve as evidence to evaluate the efficiency of markets and the extent to which behavioural or structural factors influence price formation. Additionally, by incorporating multiple emerging markets and major foreign currencies, the study enhances comparative understanding and contributes to the global discourse on market efficiency, making the research both timely and practically valuable.

1.10 Limitations of the study

Although the study provides a comprehensive examination of calendar anomalies across equity and foreign exchange markets, certain limitations should be acknowledged. First, the time periods analyzed, while extensive, vary across sectoral indices due to differences in their dates of introduction. As a result, comparisons across sectors may be influenced by unequal sample lengths and differing market phases. The exclusion of major shock periods such as the Global Financial Crisis (2007–2008) and the COVID-19 outbreak year (2020) in the foreign exchange analysis, though methodologically justified to avoid distortion, may limit insights into anomaly behaviour during extreme market stress. Additionally, the study primarily relies on dummy variable regression and volatility models such as TGARCH (1,1), which, while robust, do not incorporate macroeconomic or behavioural factors that may further explain the presence or disappearance of anomalies. Inflation rates, interest rates, and global risk sentiment indicators are not included due to inconsistent data availability across all markets and study periods. The analysis is also confined to selected stock market indices and currency pairs, leaving out wider asset classes such as commodities, bonds, and alternative financial instruments. Future research may extend the scope to incorporate additional markets, macroeconomic determinants, alternative behavioural models, and advanced machine learning techniques to enhance the explanation and prediction of anomaly patterns.

1.11 Chapterization

- **Chapter 1** focuses on the theoretical background, the literature review of the study, the research gap, the scope of the study, the need for the study, the objectives of the study, the significance of the study, the limitations of the study, and the scheme of chapterization.
- **Chapter 2** elaborates on the detailed research methodology tailored to address the objective 1 of the study and presents the results and discussion on Calendar anomalies in trading and non-trading day returns.
- **Chapter 3** focuses on the research methodology of objective 2 and results and discussion of calendar anomalies in size-based indices.
- **Chapter 4** focuses on the research methodology of objective 3 and results and discussion of Calendar Anomalies In Select Emerging Markets.
- **Chapter 5** focuses on the research methodology of objective 4 and results and discussion of Calendar Anomalies In Foreign Exchange Returns.
- **Chapter 6** presents the key findings, the conclusion, policy implications, and the contribution of the study. Additionally, it provides suggestions for future research avenues.

Chapter 2

Calendar Anomalies In Trading And Non-Trading Day Returns

2.1 Introduction

This section presents the research methodology, empirical analysis, and discussion of findings related to the presence of calendar anomalies in both trading-day and non-trading-day returns for the Nifty50 index and fourteen sectoral indices of the Indian stock market. By examining a comprehensive dataset spanning multiple years, this chapter evaluates whether systematic patterns such as Day-of-the-Week, Turn-of-the-Month, Turn-of-the-Year, Half-Month, Month-of-the-Year, Half-Year, and Week-of-the-Month effects persist in different segments of the market. The analysis further distinguishes between returns generated during active trading hours (open-to-close) and those occurring outside market hours (close-to-open), offering deeper insights into market behaviour, investor sentiment, and the efficiency of Indian equity markets.

2.2 Research methodology of objective I

The study covers the extensive period of 29 years of Nifty50 index (1st January 1996 - 31st December 2024) to examine whether calendar anomalies exist in trading day and non-trading day returns in the Indian stock market. To study the presence of calendar anomalies in trading day and non-trading day returns across 14 sectoral indices the data collected from the official website of National Stock exchange of India. The data period for each sectoral index is as follows:

- Nifty Auto Index (4th October 2011 - 31st December 2024)
- Nifty Bank Index (10th June 2005 - 31st December 2024)
- Nifty Consumer Durables Index (10th August 2021 - 31st December 2024)
- Nifty Financial Services Index (28th February 2012 - 31st December 2024)
- Nifty FMCG Index (1st February 2011 - 31st December 2024)
- Nifty Health Care Index (10th August 2021 - 31st December 2024)
- Nifty IT Index (26th August 2003 - 31st December 2024)

- Nifty Media Index (4th October 2011 - 31st December 2024)
- Nifty Metal Index (4th October 2011 - 31st December 2024)
- Nifty Oil & Gas Index (10th August 2021 - 31st December 2024)
- Nifty Pharma Index (1st February 2011 - 31st December 2024)
- Nifty Private Bank Index (15th March 2016 - 31st December 2024)
- Nifty PSU Index (1st February 2011 - 31st December 2024)
- Nifty Realty Index (20th July 2010 - 31st December 2024).

The existence of calendar anomalies in Indian stock market is studied considering Trading (Open to Close) and Non- Trading day returns (Close to Open) (Rastogi, Bang and Chaturvedula, 2011; Cornell, 1985; Rogalski, 1984). Data for sectoral indices is collected based on availability of data. Here, the study employs multiple regression with dummy variables model.

Daily returns are calculated as the natural logarithm of the ratio between consecutive closing index values, excluding non-trading days such as holidays or weekends. These close-to-close returns are further divided into trading-day and non-trading-day components. Trading-day returns are measured as the natural logarithm of the ratio of the closing price to the opening price of the same day, while non-trading-day returns are computed as the logarithmic ratio of the opening price to the previous trading day's closing price (Rogalski, 1984).

For the purpose of the study, the returns are computed as:

$$R_t = \mathrm{Ln}(P_t / P_{t-1})*100 \tag{1}$$

Where R_t is the log return of the stock or index in period t. P_t and P_{t-1} are the daily closing (opening) prices at time t and t-1 respectively. Log returns are preferred over linear returns primarily because they simplify computation, being represented as the first-order difference of logarithmic prices. Since this study applies time series data analysis techniques, non-stationary data could lead to spurious regression results. Therefore, the stationarity of the data is verified using a unit root test, where the presence of a unit root indicates that the data series is non-stationary. Augmented Dicky-Fuller test is employed to check stationarity of the return series. Since the independent variable was a point in time, it could not be represented numerically. Thus, we instead utilized dummy variables coded as either 0 or 1. To see the seasonal pattern in the data associated with the various days, weeks, months, two halves of month, turn of the month, two halves of year, and turn of the year we consider the following model:

$$R_t = \beta_1 + \beta_k D_{kt} + \varepsilon_t \quad \text{(mean equation)} \tag{2}$$

Where R_t is the index return and the D's are the dummies, taking value of 1 in the relevant calendar anomaly and 0 otherwise. To avoid the dummy variable trap, we have assigned a dummy to (m-1) category in the respective calendar anomaly studied. For example if we treat the Monday as the reference day of the week and assign dummies to the Tuesday, Wednesday, Thursday and Friday. In this context, the intercept value represents the mean return of the benchmark category. The coefficients associated with the dummy variables are referred to as differential intercept coefficients, as they indicate the extent to which the intercept of a category coded as 1 differs from that of the benchmark category.

2.2.1 Calendar Anomalies Considered for the Study

1. Day-of-the-week Effect

To examine the days of the week effect, the dummy variable regression model used is specified as follows:

$$R_t = \beta_1 + \beta_2 D_{2(Tue)} + \beta_3 D_{3(Wed)} + \beta_4 D_{4(Thu)} + \beta_5 D_{5(Fri)} + \varepsilon_t \tag{3}$$

2. Turn-of-the-Month Effect:

The turn-of-the-month effect refers to the tendency of stock prices to rise on the last trading day of the month and the first three trading days of the next month.

To test whether the turn-of-the-month effect is present in the return series, the regression model used is specified as follows:

$$R_t = \beta_1 + \beta_2 D_{2(TOM)} + \varepsilon_t \tag{4}$$

3. Turn-of-the-Year Effect:

The Turn-of-the-Year effect describes the tendency for trading volumes to rise and stock prices to increase during the last week of December and the first two weeks of January.

To test whether the turn-of-the-year effect is present in the return series, the regression model is specified as:

$$R_t = \beta_1 + \beta_2 D_{2(TOY)} + \varepsilon_t \quad (5)$$

4. Half-Monthly (Semi-Monthly) effect

It relates to higher returns in the first half of the month relative to the second half (Ariel, 1987).

To test whether the half-monthly (semi-monthly) effect is present in the return series, the regression model used is specified as:

$$R_t = \beta_1 + \beta_2 D_{2(\text{Second Half-Month})} + \varepsilon_t \quad (6)$$

5. Month of the Year

Here we analyse all months within the specified period to identify whether the mean returns of any particular month differ significantly from those of the other months.

For studying the month-of-the-year effect in the return series, the regression model used in is specified as:

$$R_t = B_1 + B_2 D_{2(\text{Feb})} + B_3 D_{3(\text{Mar})} + B_4 D_{4(\text{Apr})} + B_5 D_{5(\text{May})} + B_6 D_{6(\text{Jun})} + B_7 D_{7(\text{July})} + B_8 D_{8(\text{Aug})} + B_9 D_{9(\text{Sept})} + B_{10} D_{10(\text{Oct})} + B_{11} D_{11(\text{Nov})} + B_{12} D_{12(\text{Dec})} + \varepsilon_t \quad (7)$$

6. Half-Yearly effect

To test whether the half-yearly effect is present in the return series, the regression model used is specified as:

$$R_t = \beta_1 + \beta_2 D_{2(\text{Second Half Year})} + \varepsilon_t \quad (8)$$

7. Week-of-the-Month

To examine the week of the month effect, the dummy variable regression model used is specified as follows:

$$R_t = B_1 + B_2 D_{2(\text{Second Week})} + B_3 D_{3(\text{Third Week})} + B_4 D_{4(\text{Fourth Week})} + B_5 D_{5(\text{Fifth Week})} + \varepsilon_t \quad (9)$$

2.3 Results and Discussion

2.3.1 Existence of calendar anomalies in Nifty 50 and Sectoral Indices.

Table 2.1: Significant calendar anomalies in normal, trading and non-trading day returns.

Index	**Effect**	**Normal Day**	**Sign**	**Non-Trading Day**	**Sign**	**Trading Day**	**Sign**
Auto	DOW	Tue , Fri	Highest	Tue	Highest	Fri	Highest
	MOY	NS		NS		April	Highest
	HY	NS		Yes	Highest	NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	NS	
	TOY	NS		NS		NS	
	WOM	4	Lowest	2,3,4,	Lowest	NS	
Bank	DOW	NS		NS		Fri	Highest
	MOY	April, Sept	Highest	NS		April, Sept	Highest
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	Yes	Highest
	TOY	NS		NS		Ns	
	WOM	NS		2	Lowest	NS	
Consumer Durables	DOW	Tue	Highest	NS		NS	
	MOY	July, Sept	Highest	March, Oct	Highest	Aug	Highest
	HY	NS		NS		NS	
	HM	NS		Yes	Lowest	NS	
	TOM	Yes	Highest	NS		Yes	Highest
	TOY	NS		NS		Yes	Highest
	WOM	3,4	Lowest	NS		5	Highest
Financial Services	DOW	Tue, Fri	Highest	Tue	Highest	Fri	Highest
	MOY	Oct	Highest	NS		Nov	Highest
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	NS		Yes	Highest	NS	
	TOY	NS		NS		NS	
	WOM	NS		NS		NS	
FMCG	DOW	Tue, Wed	Highest	NS		Wed	Highest
	MOY	July	Highest	NS		Mar, June, July	Highest
	HY	NS		NS		NS	
	HM	NS		NS		NS	

	TOM	NS		Yes	Highest	NS	
	TOY	NS		NS		NS	
	WOM	5	Highest	2,5	Lowest	NS	
Health Care	DOW	NS		NS		NS	
	MOY	July	Highest	NS		July	Highest
	HY	NS		Yes	Highest	Ns	
	HM	NS		NS		NS	
	TOM	NS		Yes	Highest	NS	Highest
	TOY	NS		NS		NS	
	WOM	NS		3	Lowest	5	Highest
IT	DOW	NS		Fri	Lowest	NS	Lowest
	MOY	May	Lowest	July	Lowest	July	Highest
	HY	Yes	Highest	NS		NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	NS		Yes	Highest
	TOY	NS		NS		NS	
	WOM	NS		NS		2,3,4	Lowest
Media	DOW	Tue, Wed, Thur	Highest	Wed	Highest	Wed, Thur	highest
	MOY	NS		March	Lowest	July	highest
	HY	Yes	Highest	NS		Yes	Highest
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	Yes	Highest
	TOY	NS		NS		NS	
	WOM	2,3,4	Lowest	2	Lowest	3, 4	Lowest
Metal	DOW	NS		NS		NS	
	MOY	April	Highest	NS		April	Highest
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	NS		Yes	Highest
	TOY	NS		NS		NS	
	WOM	2, 3, 4	Lowest	2	Lowest	2, 3, 4	Lowest
Oil & Gas	DOW	NS		NS		NS	
	MOY	NS		Feb	Lowest	NS	Lowest
	HY	NS		NS		NS	
	HM	NS		Yes	Lowest	NS	Lowest
	TOM	NS		Yes	Highest	NS	Highest
	TOY	NS		NS		NS	
	WOM	NS		3,4,5	Lowest	NS	
Pharma	DOW	Tue,Wed, Fri	Highest	Wed	Highest	Wed, Fri	Highest

	MOY	April, July	Highest	April	Highest	June, July	Highest
	HY	NS		Yes	Highest	NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	Yes	Highest
	TOY	NS		NS		NS	
	WOM	5	Highest	2	Lowest	5	Highest
Private Bank	DOW	Tue	Highest	Tue	Highest	Fri	Highest
	MOY	NS		NS		NS	
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	NS		NS		NS	
	TOY	NS		NS		NS	
	WOM	NS		NS		NS	
PSU Bank	DOW	NS		NS		NS	
	MOY	NS		NS		NS	
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	Ns	
	TOY	NS		NS		NS	
	WOM	2,4	Lowest	2,3	Lowest	4	Lowest
Realty	DOW	NS		NS		NS	
	MOY	NS		Aug	Lowest	NS	
	HY	NS		NS		NS	
	HM	Yes	Lowest	NS		Yes	Lowest
	TOM	Yes	Highest	NS		Yes	Highest
	TOY	NS		NS		NS	
	WOM	2,3,4	Lowest	NS		2,3,4	Lowest
Nifty50	DOW	Wed	Highest	Tue, Wed	Highest	Wed	Highest
	MOY	Dec	Highest	Aug	Lowest	April, Nov, Dec	Highest
	HY	NS		NS		NS	
	HM	NS		NS		NS	
	TOM	Yes	Highest	Yes	Highest	Yes	Highest
	TOY	Yes	Highest	NS		NS	
	WOM	2, 3, 4	Lowest	2,3,4, 5	Lowest	2, 3, 4	Lowest

Note: 'NS' indicates statistically insignificant.

Table 2.1 summarizes the output given in **Annexure**. The analysis of the Nifty Auto Index from 4th October 2011 to 31st December 2024 provides valuable insights into the existence of calendar anomalies in both trading-day and non-trading-day returns. Using a multiple regression model with dummy variables, the study investigates variations in mean returns across different calendar timeframes, evaluated at 1%, 5%, and 10% significance levels. The Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of a unit root for all return series ($p < 0.01$). This confirms that the return series are stationary at level, ensuring that regression estimates are valid and not spurious.

The results indicate partial evidence of a Day-of-the-Week effect in the Auto sector. Tuesday and Friday returns are found to be significantly positive, suggesting that investors in the Auto segment tend to exhibit optimism toward the week's end, possibly due to increased trading activity and favourable sentiment before the weekend. In contrast, Monday returns are generally lower, consistent with the "Monday effect" documented in global markets, though significance varies. Overall, trading-day returns exhibit stronger weekday anomalies than non-trading-day returns, reflecting active behavioral trading patterns. When the month is divided into four weeks, the first week of the month exhibits positive returns significant at the 1% level, suggesting the presence of the "Week-of-the-Month effect" in the Auto index. This pattern may be attributed to the release of monthly auto sales data, fund inflows, and institutional rebalancing early in the month. The second and third weeks show mixed or insignificant coefficients, while the fourth week often records positive returns at the 10% level, likely due to end-month adjustments. These findings imply that investor activity in the Auto sector tends to cluster around the beginning and end of each month.

The monthly dummy regression highlights the April month as having significantly higher returns. The December anomaly aligns with the Turn-of-the-Year effect and fiscal-year-end optimism, while March may reflect increased sales momentum and portfolio adjustments ahead of the financial year close. Negative but insignificant returns in June indicate weaker seasonal performance during mid-year months, possibly linked to production slowdowns or monsoon-related uncertainty in demand. The study further identifies that the second half of the month consistently delivers higher mean returns, significant at the 5% level, compared to the first half. This pattern reflects liquidity-driven buying behavior following mid-month salary disbursements and fund inflows. The first half, in contrast, tends to have neutral or slightly negative returns, with limited statistical strength. The Turn-of-the-Month effect emerges as one of the most pronounced anomalies in the Nifty Auto Index. Returns observed during the last trading day of the previous month and the first three trading days of the subsequent month are significantly positive at the 1% level, indicating strong buying momentum. This is likely due to institutional rebalancing, mutual fund inflows, and portfolio adjustments timed around month-ends. The consistency of this anomaly across both trading and non-trading returns reinforces its robustness in the Auto sector.

The regression results indicate that the second half of the year (July-December) yields higher average returns, statistically significant, compared to the first half. This could be driven by festive season sales, new model launches, and stronger consumer sentiment in the Auto sector. The first half (January-June) generally reflects pre-budget uncertainties and production adjustments, leading to relatively subdued returns. Finally, the Turn-of-the-Year (TOY) effect is not evident. The Auto sector often experiences a surge in April and due to higher vehicle sales, tax-related portfolio rebalancing, and expectations of favourable policy announcements. This pattern closely aligns with international findings, particularly those of Rogalski (1984) and Rastogi et al. (2011), suggesting that investor behaviour and institutional activity contribute to year-end performance surges.

The study examines calendar anomalies in the Nifty Bank Index over the period 10th June 2005 to 31st December 2024, using multiple regression models with dummy variables for each calendar category. Significance is evaluated at 1%, 5%, and 10% levels. The regression analysis reveals no statistically significant Day-of-the-Week effect in the Banking sector. For the close-to-close (CC) and close-to-open (CO) returns, none of the weekday dummy coefficients (Tuesday through Friday) are significant even at the 10% level (all p-values > 0.20). However, for open-to-close (OC) returns, Friday exhibits a positive coefficient of 0.133883 with a p-value of 0.0591, which is marginally significant at the 10% level. This suggests a weak Friday effect, where trading-day returns tend to be higher toward the end of the week, potentially due to investor optimism and settlement activities before the weekend. Monday serves as the benchmark and records the lowest return, although not significant, aligning with the traditional pattern of slightly negative early-week sentiment. Overall, while weekday effects are largely absent, the mild Friday anomaly indicates some evidence of return clustering within the trading week. The Week-of-the-Month regression results also indicate limited support for the anomaly. For close-to-open (CO) returns, the coefficient for the second week is negative (-0.0684) and significant at the 10% level (p = 0.0945), implying that overnight returns during the second week of each month are relatively lower than those in the benchmark (first week). This may reflect short-term profit-taking following initial month-end inflows. Other weeks such as third, fourth, and fifth show no statistical significance. Both close-to-close and open-to-close models show insignificant coefficients across all weeks (p-values > 0.20). Thus, the Banking sector displays a mild second-week negative effect only in non-trading-day returns, with no strong recurring pattern across weeks.

The Month-of-the-Year analysis reveals stronger evidence of seasonal variation. For close-to-close (CC) returns, April shows a positive coefficient of 0.2719 with a p-value of 0.0351, significant at the 5% level, while September also exhibits positive returns (0.2249, p = 0.0708) significant at the 10% level. These results suggest that the Banking sector performs well during April, the start of India's new financial year, and during September, often associated with festive season optimism and higher credit activity. In the open-to-close (OC) model, April (p = 0.0173) and September (p = 0.0205) again emerge as significant at the 5% level, confirming that trading-day performance in these months is consistently strong. Other months remain statistically insignificant. For close-to-open (CO) returns, no significant coefficients are observed, implying that the anomaly is concentrated during trading hours rather than overnight. Hence, the Month-of-the-Year effect is clearly present, with April and September demonstrating statistically significant positive excess returns in trading-day activity. The Half-Month regression for the Banking sector indicates no significant difference between the first and second halves of the month across all return measures. Coefficients for second half month are statistically insignificant (p-values > 0.50) in all models, suggesting that investor activity and return generation remain fairly uniform within the month. Therefore, the Half-Month effect is absent in the Nifty Bank Index.

In contrast, the Turn-of-the-Month (TOM) effect is among the most robust and statistically significant anomalies identified. For close-to-close (CC) returns, the TOM coefficient is 0.1671 (p = 0.0096), significant at the 1% level, indicating strong positive returns around the month-end and beginning. For close-to-open (CO) returns, the coefficient is 0.0700 (p = 0.0274), significant at the 5% level, while for open-to-close (OC) returns, the coefficient is 0.0971 (p = 0.0862), significant at the 10% level. These results consistently suggest that both trading-day and overnight returns tend to rise significantly during the turn-of-the-month period. The persistence of this effect across all return definitions highlights systematic institutional fund inflows, payroll-based investments, and portfolio adjustments at month-end. The Turn-of-the-Month effect thus stands out as a strong and statistically validated anomaly in the Banking sector. The Half-Year analysis shows a positive coefficient for second half year across all models, but statistical significance is only borderline. In close-to-close (CC) returns, the coefficient (0.0817) has a p-value of 0.1098, indicating weak significance at the 10% level, implying that returns tend to be higher from July to December compared to January to June. This may reflect improved credit demand and festive spending cycles. The effect is not significant for CO or OC returns. Hence, the Half-Year effect appears to exist modestly in overall returns, but not strongly enough in intra-day or overnight segments. The Turn-of-the-Year (TOY) regression shows no significant coefficients for any return type. Although close-to-close and open-to-close intercepts are marginally positive, the dummy variable for TOY remains statistically insignificant (p-values > 0.57).

The Augmented Dickey-Fuller (ADF) test confirmed that the return series for the Consumer Durables sector is stationary at level, with all three ADF test statistics (−26.26, −26.87, and −27.78) significant at the 1% level. Hence, the series is free from unit root issues and suitable for regression analysis of calendar anomalies. The day-of-the-week regression reveals no significant evidence of abnormal returns across trading days. The constant term (C = −0.0023, p = 0.978) indicates no consistent bias in average returns. Although Tuesday shows a mildly positive coefficient (0.2082) with a near-significant p-value (0.0689), it does not cross the 5% threshold. This suggests a weak tendency for higher Tuesday returns, but not statistically conclusive. Returns on Wednesday (0.0749), Thursday (0.0017), and Friday (0.0457) are all statistically insignificant (p > 0.5). The overall F-statistic (1.118, p = 0.346) supports the absence of systematic weekday effects. Thus, the Consumer Durables sector displays no clear Day-of-the-Week anomaly, though Tuesday may have slightly positive momentum. Monthly regressions indicate some seasonal patterns. In the Close-to-Close (CC) model, July ($\beta = 0.4053$, p = 0.0302) and August ($\beta = 0.3668$, p = 0.0399) exhibit significantly higher returns, suggesting strong positive performance during mid-year. Similarly, September ($\beta = 0.3065$, p = 0.081) approaches significance. In the Close-to-Open (CO) specification, March ($\beta = 0.1900$, p = 0.0412) and October ($\beta = 0.1901$, p = 0.0285) show significant positive coefficients, indicating above-average opening returns in these months. The Open-to-Close (OC) model identifies August ($\beta = 0.2802$, p = 0.0784) as marginally significant, implying intra-day gains during this month. These findings suggest a partial Month-of-the-Year effect, with July–October being stronger months for returns, possibly linked to seasonal demand and festival-driven sales in the sector.

The second half of the year shows positive but statistically insignificant coefficients across all models. For example, in the CC model, $\beta = 0.1009$ ($p = 0.1669$), and in the CO model, $\beta = 0.0392$ ($p = 0.2733$). Though the direction is positive suggesting marginally better returns in the latter half of the year there is insufficient evidence to confirm a Half-Year effect. In the half-month regressions, the CO model shows a negative and nearly significant coefficient for the second half of the month ($\beta = -0.0695$, $p = 0.0504$), indicating that returns tend to decline toward month-end. The CC and OC models are insignificant ($p = 0.332$ and $p = 0.990$, respectively). This pattern suggests a weak inverse half-month effect, where the first half tends to outperform the latter half.

The Turn-of-the-Month effect is strongly significant in this sector. In the CC regression, the coefficient for TOM is positive and significant ($\beta = 0.2418$, $p = 0.008$), implying that investors earn notably higher returns during the few days surrounding the turn of the month. Similarly, the OC model confirms this pattern ($\beta = 0.2112$, $p = 0.0097$), while the CO model is insignificant. These results highlight a robust TOM effect in the Consumer Durables sector, possibly driven by end-of-month institutional repositioning or retail investor optimism during salary-credit periods. Turn-of-the-Year analysis reveals positive coefficients across all models but without statistical significance at the 5% level. In the OC model, TOY shows a marginal p-value ($\beta = 0.2433$, $p = 0.063$), suggesting a weak indication of higher returns during the year transition. Overall, the evidence for a Turn-of-the-Year effect is minimal, though returns tend to be mildly positive at year-end.

The weekly regressions uncover significant variations in certain weeks. In the CC model, both the third week ($\beta = -0.2415$, $p = 0.0428$) and fourth week ($\beta = -0.2357$, $p = 0.0471$) display significantly lower returns compared to the first week, while the second and fifth weeks are insignificant. This implies that returns dip during the mid-to-late weeks of each month. The OC model partially supports this trend, with the fifth week ($\beta = 0.2000$, $p = 0.087$) showing positive but weak significance. These findings indicate a Week-of-the-Month anomaly where returns fluctuate within the month, with weakness concentrated in the middle weeks.

The Financial Services sector was first tested for stationarity using the Augmented Dickey–Fuller test, where all three ADF statistics were significant at the **1% level**, confirming that the return series is stationary and suitable for anomaly analysis. The regression analysis for the day-of-the-week effect reveals limited evidence of significant weekday patterns in the Financial Services sector. In the Close-to-Close (CC) model, the Tuesday coefficient (β = 0.1457, p = 0.0592) is significant at the 10% level, suggesting relatively higher returns on Tuesdays compared to the base day (Monday). Similarly, the Friday coefficient (β = 0.1311, p = 0.0912) is also significant at the 10% level, implying modest positive end-of-week returns. The Wednesday and Thursday coefficients are positive but statistically insignificant. The Close-to-Open (CO) model further supports this tendency, with Tuesday again marginally significant (β = 0.0809, p = 0.0511) at the 10% level, indicating slightly higher opening returns on Tuesdays. The Open-to-Close (OC) model reveals a Friday effect, with β = 0.1307 and p = 0.0462, significant at the 5% level, suggesting intraday optimism or positive investor sentiment at week's end. Collectively, these results indicate partial evidence of a Tuesday and Friday effect, where the Financial Services sector tends to yield marginally higher returns at the beginning and end of the trading week.

The monthly regression results display weak evidence of a Month-of-the-Year effect. In the CC model, October (β = 0.2073, p = 0.0868) and November (β = 0.1971, p = 0.104) are significant at the 10% level, indicating relatively higher returns in the post-monsoon and pre-festive period, aligning with seasonal business cycles and corporate announcements. In the CO model, none of the months exhibit statistical significance, while in the OC model, November (β = 0.1762, p = 0.0855) again appears significant at the 10% level, reinforcing slightly positive returns around this period. These findings point toward a mild seasonal effect concentrated in October and November, likely reflecting market optimism preceding India's festive season and year-end portfolio adjustments.

The Half-Year regression suggests no statistically significant difference in returns between the first and second halves of the year. All three models CC (β = 0.0404, p = 0.4090), CO (β = 0.0263, p = 0.3162), and OC (β = 0.0141, p = 0.7336) are insignificant even at the 10% level. However, the coefficients are positive in direction, implying slightly higher returns in the latter half of the year, although not strong enough to confirm a Half-Year anomaly. The half-month regressions reveal no substantial anomalies. The coefficient for the second half of the month is negative across all three models CC (β = −0.0260, p =

0.594), CO (β = −0.0077, p = 0.769), and OC (β = −0.0183, p = 0.657) indicating marginally lower returns in the latter half of each month, though not statistically significant. Thus, there is no evidence of a Half-Month effect in the Financial Services sector.

The Turn-of-the-Month effect shows mixed evidence across models. In the CO model, the coefficient for TOM (β = 0.0578, p = 0.0812) is significant at the 10% level, suggesting higher opening returns during the few days around month-end and beginning. However, the CC (β = 0.0565, p = 0.360) and OC (β = −0.0013, p = 0.980) models show no statistical significance. The evidence therefore suggests a weak but positive Turn-of-the-Month effect, particularly in opening prices, consistent with liquidity inflows and institutional rebalancing at month transitions.

The Turn-of-the-Year results show no significant effect at conventional levels. The coefficients for TOY in the CC (β = −0.0519, p = 0.612), CO (β = 0.0157, p = 0.775), and OC (β = −0.0677, p = 0.435) models are all insignificant. The signs vary across models, suggesting that the Financial Services sector does not exhibit systematic return differences at the year's transition, and hence lacks a Turn-of-the-Year anomaly.

The Week-of-the-Month regression shows no strong evidence of intra-month patterns. The coefficients for the second, third, and fourth weeks are all negative in the CC model, with the fourth week (β = −0.1255, p = 0.115) being marginally significant at the 10% level, indicating lower returns during the end weeks of the month. Other weeks, including the fifth week, remain statistically insignificant. The CO and OC models do not display any significant results. This suggests a mild fourth-week effect, where returns slightly decline before month-end, potentially due to profit-taking or reduced trading volumes.

The FMCG sector's return series was first tested for stationarity using the Augmented Dickey–Fuller test. All three ADF test statistics are significant at the 1% level, confirming that the return data is stationary and suitable for regression analysis of calendar effects. The anomalies are examined using Trading-Day (OC), Non-Trading-Day (CO), and Close-to-Close (CC) returns.

The FMCG sector shows partial evidence of weekday anomalies. In CC returns, Wednesday exhibits a significant positive effect (β = 0.1336, p = 0.0183), indicating higher

mid-week returns, significant at the 5% level. Tuesday is also positive and marginally significant at the 10% level (β = 0.0968, p = 0.0871), suggesting moderately favorable Tuesday returns. Friday and Thursday coefficients are positive but not significant.
In CO returns, no weekday is significant, meaning overnight returns do not show a weekday pattern. In OC returns, Wednesday again is significant at the 5% level (β = 0.1039, p = 0.0435), indicating strong intraday positive movement mid-week. Overall, the FMCG index demonstrates a robust Wednesday effect (significant in both CC and OC returns), and a weak Tuesday effect at the 10% level.

The FMCG sector shows limited monthly seasonality. In CC returns, July is the only month near significance with a positive coefficient (β = 0.1566, p = 0.0718), indicating marginally higher FMCG returns in July, significant at the 10% level. No other months show significance. In CO returns, none of the monthly dummies are significant, indicating absence of seasonality in overnight returns. In OC returns, March shows a significant positive effect at the 5% level (β = 0.1594, p = 0.0473), and June (p = 0.0944) and July (p = 0.0985) are significant at the 10% level, suggesting strong intraday performance during early monsoon and Q1 results season. Thus, the FMCG sector shows a March intraday effect (5%) and June–July intraday effects (10%), but no broad monthly anomaly across the three models.

The Half-Year dummy shows no statistically significant effect in any model. The coefficients for the second half of the year are negative in CC (p = 0.4785) and OC (p = 0.1383) and positive in CO (p = 0.1747), but none reach even 10% significance. Therefore, the FMCG sector does not exhibit a Half-Year anomaly. The results show no evidence of a Half-Month effect. Second-half coefficients are insignificant in CC (p = 0.5177), CO (p = 0.7795), and OC (p = 0.3917). Hence, the FMCG sector's returns do not differ systematically between the first and second half of the month.

The FMCG sector shows weak evidence of a TOM effect. In CO returns, the TOM coefficient is positive and significant at the 10% level (β = 0.0355, p = 0.0951), suggesting stronger opening returns during the month-transition period, possibly reflecting the impact of salary credits, systematic investments, and institutional rebalancing. However, CC and OC returns do not show significance. Thus, the FMCG sector exhibits a mild TOM effect, specifically in overnight returns. No Turn-of-the-Year anomaly is observed. TOY coefficients across CC ($p = 0.8379$), CO ($p = 0.5033$), and OC ($p = 0.9034$) are insignificant with very small magnitudes. This indicates that year-end trading does not systematically affect FMCG returns.

The Week-of-the-Month results show stronger evidence of anomalies compared to other seasonal patterns. In CC returns, the Fifth Week is marginally significant at 10% ($\beta = 0.1129$, $p = 0.0804$), indicating relatively higher returns when a month contains an extra week. In CO returns, the Second Week shows a significant negative effect at the 1% level ($\beta = -0.0738$, $p = 0.0070$), indicating lower overnight returns early in the month. The fifth week approaches 10% significance ($p = 0.0675$). In OC returns, the Fifth Week displays a strong positive effect at the 1% significance level ($\beta = 0.1685$, $p = 0.0041$), making it the strongest and most significant anomaly in the FMCG sector.

The Health Care sector's return series was first examined for stationarity using the Augmented Dickey–Fuller test. All three ADF test statistics are highly significant at the 1% level, confirming that the return data is stationary. This validates the use of regression analysis for testing calendar anomalies. The Health Care index shows very weak evidence of weekday effects. In CC returns, Wednesday displays a marginally significant positive effect at the 10% level ($\beta = 0.1668$, $p = 0.1035$), suggesting slightly higher mid-week performance. No other weekdays are significant. CO returns show no weekday significance, confirming that overnight price movements are not influenced by trading-day patterns. Similarly, OC returns show no significant weekday effects, as none of the coefficients reach even the 10% significance level. Overall, the Health Care sector exhibits only a weak Wednesday effect in CC returns, indicating limited day-of-the-week seasonality.

The Health Care sector reveals minimal monthly seasonality. In CC returns, July exhibits a clear anomaly, with a significant positive coefficient at the 5% level ($\beta = 0.3947$, $p = 0.0181$), indicating strong performance in July. No other months are significant. In CO returns, none of the monthly dummy variables are significant, showing no overnight monthly pattern. In OC returns, July again emerges significant at the 5% level ($\beta = 0.3736$, $p = 0.0175$), and June is positive but only marginally significant at 10% ($p = 0.131$). Thus, the Health Care sector exhibits a consistent July effect (stronger returns in July in both CC and OC), and weak evidence of a June intraday pattern.

The Half-Year effect shows limited and inconsistent significance. In CC and OC returns, the Half-Year dummy is insignificant (p = 0.3599 and 0.8211), showing no clear difference between the two halves of the year. However, in CO returns, the second half of the year shows a positive and marginally significant effect at the 10% level (β = 0.0459, p = 0.0914). This indicates higher overnight returns in the second half of the year, though the pattern is not reflected in intraday or full-day returns. Overall, the sector shows a weak Half-Year effect, limited to CO returns.

No strong Half-Month anomalies are observed. The second-half dummy is insignificant across CC (p = 0.9583), CO (p = 0.2122), and OC (p = 0.6192) models. Although OC returns show a borderline significant intercept (p = 0.0566), the dummy variable itself is not significant. Thus, the Health Care sector shows no meaningful difference between first-half and second-half monthly returns.

The Turn-of-the-Month effect appears only in overnight returns. In CC and OC returns, TOM is insignificant. However, in CO returns, TOM is positive and marginally significant at the 10% level (β = 0.0636, p = 0.0632). This suggests that the opening prices following the month-end period tend to be stronger, possibly reflecting end-of-month fund rebalancing and SIP flows. Overall, the Health Care sector shows a weak but consistent TOM effect restricted to CO returns.

The Turn-of-the-Year anomaly is not strongly supported, although two models show borderline results. In CC returns, TOY is positive and marginally significant at the 10% level (β = 0.2086, p = 0.1106). In CO returns, TOY again shows 10% significance (β = 0.0883, p = 0.105). However, OC returns show no significance (p = 0.3283). Thus, evidence points to a weak TOY effect, mainly affecting opening prices and CC returns, consistent with year-end investment realignment.

The Health Care sector shows stronger evidence of Week-of-the-Month anomalies compared to other seasonal patterns. In CC returns, although no individual week is significant at traditional levels, the overall model is significant at 5% (Prob(F) = 0.0450). This implies that weekly positioning within the month influences returns collectively.

In CO returns, the Third Week is significant at the 5% level ($\beta = -0.0990$, $p = 0.0266$), indicating lower overnight returns in the third week of the month. In OC returns, the Fifth Week shows a strong and significant effect at the 5% level ($\beta = 0.2187$, $p = 0.0473$), marking it as the most prominent anomaly in the Health Care sector. Thus, the sector displays a Third-Week negative overnight effect and a Fifth-Week positive intraday effect, making week-based anomalies the most pronounced among all tested patterns.

The results for the IT sector provide strong preliminary evidence of stationarity, as the Augmented Dickey-Fuller (ADF) statistics are extremely large in magnitude (around –72) with p-values < 0.01, confirming that the return series do not contain a unit root and are suitable for anomaly testing. Beginning with the Day-of-the-Week Effect, the Close-to-Close and Open-to-Close regressions show that none of the weekday coefficients are significant even at the 10% level, indicating no weekday return pattern in normal trading hours. However, a noteworthy finding emerges in the Open-to-Close series, where Friday exhibits a statistically significant negative return ($p = 0.0367 < 0.05$), signalling a mild Friday Effect, consistent with risk-averse unwinding positions or pre-weekend profit-taking. Conversely, in the Open-to-Open model, Friday shows a positive but only marginally significant effect ($p = 0.1112$), suggesting that any favorable Friday overnight drift is not strong enough to affect daytime returns. Moving to the Month-of-the-Year Effect, the IT sector does not exhibit strong seasonal patterns in either CC, CO, or OC returns. However, the month of May shows a marginally significant negative effect ($p = 0.0617$) in the Close-to-Close model, hinting at a weak "Sell in May" pattern, although the effect is not robust across return measures. The most notable month-level effect appears in the Open-to-Open (OC) model, where July shows a highly significant positive return ($p = 0.0057 < 1\%$), suggesting that July consistently yields strong overnight gains for IT stocks possibly reflecting earnings announcements, monsoon-related optimism in consumption sectors, or international cues from global tech markets.

The Half-Year Effect (Second Half vs. First Half) reveals only marginal evidence of seasonality, with the Close-to-Close return showing a borderline positive effect in the second half of the year ($p = 0.0511$), indicating slightly higher returns from July–December, though not strong enough to be conclusive at the 5% significance level. The Half-Month Effect (second half vs. first half of each month) shows no significant anomaly across all return measures, with all p-values well above 10%, implying the IT sector does not exhibit systematic mid-month patterns. In contrast, the Turn-of-the-Month (TOM) Effect provides meaningful evidence of anomaly behaviour. The TOM coefficient in the Close-to-Close model is marginally positive ($p = 0.0685 < 10\%$), indicating slightly higher returns during the 2 days before and after month-end, consistent with institutional liquidity cycles. More importantly, the Open-to-Open model displays a strongly significant TOM effect ($p = 0.0075 < 1\%$), demonstrating that overnight returns around month-end are substantially higher, likely driven by fund-manager window-dressing and NAV reporting behaviour, which disproportionately affects IT stocks given their index weight and institutional ownership.

The Turn-of-the-Year (TOY) Effect shows no significant behaviour for any of the three return measures, suggesting that the IT sector does not display the classic January Effect commonly found in developed markets. Finally, the Week-of-the-Month Effect provides the clearest and most consistent anomaly in the IT sector. While CC and CO returns remain insignificant across weeks, the Open-to-Open model reveals strongly negative returns in the 2nd, 3rd, and 4th weeks, all significant at the 5% level ($p = 0.0337$, 0.0434, and 0.0472 respectively). This pattern suggests the presence of a mid-month decline, possibly capturing corporate settlement cycles, F&O rollover positioning, or scheduled institutional selling. The strongly significant negative coefficients highlight that these weeks systematically yield lower overnight returns, making the Week-of-the-Month anomaly one of the most robust findings for the IT sector.

Overall, the IT sector shows limited evidence of standard weekday and month-of-year anomalies, but exhibits strong and economically meaningful anomalies in specific windows namely the July effect (overnight), a highly significant Turn-of-the-Month effect (overnight), and persistent mid-month negative returns across the 2nd, 3rd, and 4th weeks. These results underscore that anomaly behaviour in IT is concentrated around overnight institutional activity rather than regular trading hours.

The Media index return series is confirmed as stationary through extremely large negative Augmented Dickey-Fuller statistics (–56 to –57) with p-values < 0.01, establishing that the data is suitable for regression-based anomaly testing. The results for the Day-of-the-Week Effect show that in the Close-to-Close returns, Wednesday ($p = 0.0181$) and Thursday ($p = 0.0373$) are significantly positive at the 5% level, while Tuesday is marginally positive at the 10% level ($p = 0.0815$). This indicates that the Media sector experiences a mid-week return build-up, suggesting improved price discovery or information release during mid-week. The Open-to-Close returns do not show strong weekday effects, although Wednesday is weakly significant at the 10% level ($p = 0.0865$), hinting at slightly higher intraday returns mid-week. In contrast, the Open-to-Open (overnight) returns reveal a marginally positive Thursday effect at the 10% level ($p = 0.0544$) and a weak Wednesday effect ($p = 0.0777$), indicating that mid-week overnight gains exist but are not as strong as the CC findings.

For the Month-of-the-Year anomaly, the Media sector shows almost no significant monthly pattern in CC or OC returns. However, the Open-to-Close model detects a significant negative March effect at the 1% level ($p = 0.0054$), indicating that March consistently produces weaker intraday performance for Media stocks, possibly due to financial-year-end adjustments and muted advertising revenues. A key finding in the OC model is the positive July effect ($p = 0.0474 < 5\%$), suggesting that overnight returns in July are stronger, potentially reflecting improved quarterly earnings or favourable industry announcements during this period.

The Half-Year Effect reveals moderate seasonal behaviour: the Close-to-Close model shows a significant positive return in the second half of the year ($p = 0.049$), indicating that July–December yields better overall returns for the Media sector compared to January–June. In the overnight (OC) model, the second half also shows marginal significance at the 10% level ($p = 0.0896$), suggesting that the improvement is partly due to stronger overnight movements. However, the intraday CO returns show no seasonal difference. The Half-Month Effect does not produce any statistically significant results, indicating that Media stocks do not experience systematic differences between the first and second halves of the month in any return measure.

A very strong and economically meaningful Turn-of-the-Month (TOM) effect is found across all three return measures. The CC returns show a highly significant positive TOM effect ($p = 0.0003 < 1\%$), while both the CO ($p = 0.0232 < 5\%$) and OC ($p = 0.0043 < 1\%$) regressions confirm this pattern. This suggests that Media stocks deliver consistently higher returns during the window surrounding the month-end, likely driven by institutional fund flows, portfolio rebalancing, and NAV-related adjustments. In contrast, the Turn-of-the-

Year (TOY) effect is entirely absent, with all p-values well above 10%, implying that the Media sector does not exhibit a January or year-end seasonal pattern.

The Week-of-the-Month anomaly is among the strongest findings for the Media index. In the CC model, the 2nd ($p = 0.0102$), 3rd ($p = 0.0019$), and 4th weeks ($p = 0.0024$) all show significant negative returns, indicating consistent mid-month declines. This pattern is also visible in the CO model, where the 2nd week is significantly negative at the 1% level ($p = 0.0015$) and the 3rd and 4th weeks are marginally negative at the 10–12% level. Similarly, the OC model shows strongly negative 3rd ($p = 0.0088$) and 4th week ($p = 0.0098$) overnight returns, confirming that the Media sector systematically experiences mid-to-late month weakness, possibly related to advertising cycle patterns, revenue booking schedules, or liquidity withdrawal by institutional investors.

The return series of the Metal index is confirmed to be stationary, as all Augmented Dickey–Fuller test statistics are extremely negative (–38 to –59) and statistically significant at the 1% level, eliminating concerns of non-stationarity or spurious regression effects. Examining the Day-of-the-Week anomaly, none of the weekday dummy variables for Close-to-Close (CC), Close-to-Open (CO), or Open-to-Close (OC) returns are statistically significant at the 1%, 5%, or 10% levels. This indicates that Metal stocks do not exhibit any systematic weekday return behaviour. All weekday coefficients remain small and statistically insignificant, and the corresponding F-statistics also confirm the absence of a weekly seasonal pattern.

For the Month-of-the-Year anomaly, most monthly coefficients are insignificant across CC, CO, and OC returns. The only exception is April in the OC model, which shows a positive and marginally significant effect at the 10% level ($p = 0.0501$), indicating slightly stronger overnight returns during April. Similarly, the CC model shows a borderline positive April effect ($p = 0.0547$), suggesting mild strength around April but only at the 10% level. Overall, the Metal sector does not display strong or consistent monthly seasonality.

Moving to the Half-Year effect, none of the models show significance. Both CC and CO returns have statistically insignificant differences between the two halves of the year, and although OC returns are negative with a significant constant term, the half-year dummy remains insignificant. Thus, there is no evidence of a semi-annual seasonal return pattern in the Metal sector.

The Half-Month anomaly also fails to show statistical significance across all three return measures. Neither CC, CO, nor OC returns produce meaningful differences between the first and second halves of the month. Coefficients remain small, and p-values exceed the 10% threshold throughout, indicating the absence of a half-month pattern.

A strong and economically meaningful pattern appears for the Turn-of-the-Month (TOM) anomaly. The TOM coefficient is highly significant for CC returns at the 1% level (p = 0.0001) and for OC returns also at the 1% level (p = 0.0001). This suggests that the Metal sector delivers substantial positive returns during the days surrounding the month-end, capturing return bursts particularly in overnight prices. The CO (intraday) model shows no significance, implying that the TOM effect in Metals is driven mainly by overnight adjustments, likely influenced by institutional rebalancing, fund flows, or liquidity cycles at month-end. This TOM effect is one of the strongest seasonal patterns detected in the Metal index.

In contrast, the Turn-of-the-Year (TOY) effect is entirely absent, as none of the models show statistical significance. This indicates no special return behaviour around the New Year transition for Metal stocks.

The Week-of-the-Month anomaly produces some of the most striking results for the Metal sector. In the CC model, the 2nd week (p = 0.0061), 3rd week (p = 0.0016), and 4th week (p = 0.0004) all show significant negative returns, indicating a persistent mid-to-late month decline pattern. This suggests that the Metal sector tends to weaken after the first week of the month. The CO (intraday) results show only marginal significance for the 2nd week at the 10% level (p = 0.0782), suggesting slightly weaker intraday returns early in the month. The OC (overnight) model strongly reinforces the CC findings: the 2nd week (p = 0.0253), 3rd week (p = 0.0028), and 4th week (p = 0.0008) are all significantly negative, confirming consistent overnight declines during the middle and later parts of the month. This represents one of the strongest and most persistent anomalies within the Metal sector, possibly reflecting liquidity cycles, margin settlement patterns, or industry-specific cash flow timing.

The return series of the Metal index is confirmed to be stationary, as all Augmented Dickey-Fuller test statistics are extremely negative (–38 to –59) and statistically significant at the 1% level, eliminating concerns of non-stationarity or spurious regression effects. Examining the Day-of-the-Week anomaly, none of the weekday dummy variables for Close-to-Close (CC), Close-to-Open (CO), or Open-to-Close (OC) returns are statistically significant at the 1%, 5%, or 10% levels. This indicates that Metal stocks do not exhibit any systematic weekday return behaviour. All weekday coefficients remain small and statistically insignificant, and the corresponding F-statistics also confirm the absence of a weekly seasonal pattern.

For the Month-of-the-Year anomaly, most monthly coefficients are insignificant across CC, CO, and OC returns. The only exception is April in the OC model, which shows a positive and marginally significant effect at the 10% level ($p = 0.0501$), indicating slightly stronger overnight returns during April. Similarly, the CC model shows a borderline positive April effect ($p = 0.0547$), suggesting mild strength around April but only at the 10% level. Overall, the Metal sector does not display strong or consistent monthly seasonality.

Moving to the Half-Year effect, none of the models show significance. Both CC and CO returns have statistically insignificant differences between the two halves of the year, and although OC returns are negative with a significant constant term, the half-year dummy remains insignificant. Thus, there is no evidence of a semi-annual seasonal return pattern in the Metal sector.

The Half-Month anomaly also fails to show statistical significance across all three return measures. Neither CC, CO, nor OC returns produce meaningful differences between the first and second halves of the month. Coefficients remain small, and p-values exceed the 10% threshold throughout, indicating the absence of a half-month pattern.

A strong and economically meaningful pattern appears for the Turn-of-the-Month (TOM) anomaly. The TOM coefficient is highly significant for CC returns at the 1% level ($p = 0.0001$) and for OC returns also at the 1% level ($p = 0.0001$). This suggests that the Metal sector delivers substantial positive returns during the days surrounding the month-end, capturing return bursts particularly in overnight prices. The CO (intraday) model shows no significance, implying that the TOM effect in Metals is driven mainly by overnight adjustments, likely influenced by institutional rebalancing, fund flows, or liquidity cycles at month-end. This TOM effect is one of the strongest seasonal patterns detected in the Metal index. In contrast, the Turn-of-the-Year (TOY) effect is entirely absent, as none of the models show statistical significance. This indicates no special return behaviour around the New Year transition for Metal stocks.

The Week-of-the-Month anomaly produces some of the most striking results for the Metal sector. In the CC model, the 2nd week ($p = 0.0061$), 3rd week ($p = 0.0016$), and 4th week ($p = 0.0004$) all show significant negative returns, indicating a persistent mid-to-late month decline pattern. This suggests that the Metal sector tends to weaken after the first week of the month. The CO (intraday) results show only marginal significance for the 2nd week at the 10% level ($p = 0.0782$), suggesting slightly weaker intraday returns early in the month. The OC (overnight) model strongly reinforces the CC findings: the 2nd week ($p = 0.0253$), 3rd week ($p = 0.0028$), and 4th week ($p = 0.0008$) are all significantly negative, confirming consistent overnight declines during the middle and later parts of the month. This represents one of the strongest and most persistent anomalies within the Metal sector, possibly reflecting liquidity cycles, margin settlement patterns, or industry-specific cash flow timing.

The Oil & Gas index returns are confirmed to be stationary as all Augmented Dickey–Fuller statistics are extremely negative (–17 to –30 range) and statistically significant at the 1% level, ensuring that the regression results are reliable and free from unit-root distortions. Turning to the Day-of-the-Week anomaly, the results do not show any statistically significant weekday effects across Close-to-Close (CC), Close-to-Open (CO), or Open-to-Close (OC) returns. Although point estimates vary slightly for example, Friday shows negative returns in CC (–0.135) and OC (–0.176) none of these effects are significant even at the 10% level, and the F-statistics confirm the absence of overall weekday seasonality. Thus, Oil & Gas stocks do not exhibit a day-of-the-week pattern.

For the Month-of-the-Year anomaly, the CC and OC models show no meaningful month effects. All monthly dummies have p-values far above 0.10, indicating the absence of strong or moderate monthly seasonality. The CO model, however, shows a weak February effect, where February returns are negative and marginally significant at the 10% level ($p = 0.0577$). This suggests mildly lower intraday returns during February, though the effect is not robust enough to qualify as a strong anomaly. Apart from this, no other months exhibit statistically significant deviations, confirming generally stable month-to-month performance in the sector.

The Half-Year anomaly is entirely absent, as the second-half dummy is statistically insignificant in CC ($p = 0.818$), CO ($p = 0.743$), and OC ($p = 0.921$) models. This indicates that returns do not meaningfully differ between the first and second halves of the year.

In contrast, the Half-Month anomaly shows one significant effect. The CO (intraday) model reveals that returns are significantly lower in the second half of the month, with a coefficient of –0.0817 significant at the 5% level ($p = 0.0375$). This provides moderate evidence of intraday weakness in late-month Oil & Gas trading. However, neither CC nor OC returns show significance, indicating that this anomaly is confined to intraday price movements.

The Turn-of-the-Month (TOM) effect exhibits a clear and statistically significant anomaly in the CO model. The TOM coefficient is positive (0.10034) and significant at the 5% level ($p = 0.044$), implying stronger intraday returns during the days surrounding the month-end. This suggests institutional flows or liquidity effects boost trading activity in the Oil & Gas sector specifically during TOM days. Conversely, TOM is not significant in the CC and OC models, indicating that the anomaly does not extend to total or overnight returns. The Turn-of-the-Year (TOY) effect is absent in all models. Neither CC, CO, nor OC returns display statistical significance, suggesting no special return behaviour during the year-end transition period for this sector.

A strong pattern re-emerges in the Week-of-the-Month anomaly. The CC model shows a nearly significant third-week effect at 10% ($p = 0.1037$), but it is not strong enough to be conclusive. More importantly, the CO (intraday) model presents clear evidence of weekly seasonality. The third week of the month shows significantly negative returns at the 1% level ($p = 0.0094$), while the fourth and fifth weeks are weakly significant at the 10% level ($p = 0.0837$ and 0.0852), respectively. This pattern indicates that intraday Oil & Gas returns tend to weaken progressively in the latter part of the month. The OC model shows no significant effects, implying that this anomaly is driven exclusively by intraday price adjustments.

For the Pharma sector, clear day-of-the-week effects appear primarily in close-to-close (CC) and open-to-close (OC) returns. In the CC model, Wednesday (p=0.0155) and Friday (p=0.0089) show significant positive returns at the 5% and 1% levels, respectively, indicating that these two days yield unusually strong profits compared to Monday (the benchmark). Tuesday is marginally significant at the 10% level (p=0.0859), suggesting slightly higher but weaker evidence of excess returns. In the CO and OC regressions, none of the weekdays show significance except Friday in OC (p=0.0063), confirming that Friday in Pharma markets tends to generate disproportionately higher intraday profits. The overall F-statistic for the CC model is significant at the 5% level, proving that day-of-the-week anomalies exist in the Pharma sector.

The Pharma sector displays selective monthly anomalies. In the CC regression, April (p=0.0179) is significant at the 5% level, while July (p=0.0519) is significant at the 10% level, implying strong positive returns during these months. All other months show no significance. In the CO and OC models, April again approaches significance (p≈0.058–0.103), but does not meet the 5% threshold, although June and July in OC are marginally significant at the 10% level. Overall, the F-statistic in the CC and OC models is significant, indicating that month-of-the-year effects are present, primarily driven by April and July.

The half-year dummy (1 = July–December) shows no significant effect in the CC or OC regressions, as p-values exceed 0.60 and 0.80, respectively. However, in the CO model, the half-year effect is marginally significant at the 10% level (p=0.088), suggesting that intraday returns from open-to-close are slightly higher in the second half of the year. The overall evidence is weak, showing no strong half-year anomaly in the Pharma sector.

The second-half-of-month dummy (days 16–end) does not show any statistical significance in any of the three return models. With p-values between 0.74 and 0.92, there is no evidence of a half-month anomaly in the Pharma index. This indicates that returns do not systematically vary between the first and second halves of each month.

The Turn-of-the-Month effect is strong and highly significant across all three models for Pharma. In CC returns, the TOM coefficient is significant at the 1% level (p=0.0002); in CO returns at the 1% level (p=0.0102); and in OC returns at the 1% level (p=0.0057). This means that Pharma stocks exhibit sharply higher returns around the last trading day of the month and first three days of the next month. The effect is robust across intraday and daily returns, making TOM one of the strongest anomalies in the Pharma sector.

The Turn-of-the-Year dummy shows no statistical significance in CC, CO, or OC returns, with p-values above 0.13. This indicates that, unlike TOM, the Pharma sector does not display clear return patterns around the New Year period. No meaningful TOY anomaly is present.

The week-of-the-month results reveal limited significance. In the CC regression, the overall F-statistic is significant, but none of the week dummies are significant at the 5% level, although the fifth week (p=0.0973) is marginally significant at the 10% level, suggesting occasional positive returns when a month contains five trading weeks. In the CO model, no week shows statistical significance. In the OC model, only the fifth week is significant at the 5% level (p=0.0406), indicating unusually strong open-to-close returns in markets that experience a fifth trading week. Overall, week-of-the-month anomalies exist but are weak and mostly driven by the rare fifth week effect.

For the Private Bank Index, the day-of-the-week regression reveals a limited and weak weekday effect, with significance appearing only for Tuesday. In the close-to-close (CC) model, Tuesday shows a positive and statistically significant coefficient at the 1% level (p=0.0065), indicating that Tuesday yields significantly higher daily returns compared to Monday, the benchmark day. Wednesday, Thursday, and Friday have positive coefficients but remain statistically insignificant at the 10% level. In the open-to-close (CO) model, the Tuesday effect persists, significant at the 5% level (p=0.0159), suggesting that intraday (trading-hour) returns are consistently stronger on Tuesdays. However, the open-to-close regression shows no significance for Wednesday, Thursday or Friday, and the Friday coefficient in the open-to-close model is insignificant (p=0.621). In the open-to-close (OC) model there is no weekday significance, except that Friday approaches significance at the 10% level (p=0.0531), suggesting a weak tendency for higher overnight returns into Friday. The F-statistic is significant only for the CO model (p=0.0327), confirming that intraday returns exhibit the strongest weekday pattern, driven mainly by Tuesday. Overall, the Private Bank Index displays a Tuesday effect, with no strong evidence for other weekday anomalies.

The month-of-the-year regressions for the Private Bank Index reveal no statistically significant monthly effects across any of the three return measures. All monthly dummy variables in the CC, CO, and OC regressions have p-values well above the 10% threshold, indicating that seasonal monthly patterns are absent. The F-statistics are also insignificant in all three cases (p-values between 0.56 and 0.96), confirming that the Private Bank sector does not display systematic monthly seasonality. Thus, returns do not consistently rise or fall in any specific month of the year.

The half-year anomaly (January–June vs. July–December) also shows no significant effect in the Private Bank Index. In all three models (CC, CO, OC), the second-half-year dummy is statistically insignificant, with p-values of 0.48, 0.36, and 0.82 respectively. Even though the constant term in the CO model is significant, the half-year dummy is not, indicating that returns do not differ meaningfully between the first and second halves of the year. Therefore, no half-year anomaly is present.

Similarly, the half-month regressions show no evidence of a half-month anomaly. The dummy for the second half of the month is insignificant across CC (p=0.412), CO (p=0.849), and OC (p=0.399) models. This confirms that returns do not follow a pattern that alternates between the first and second halves of each month in the Private Bank Index.

The TOM effect, which is strong in many financial markets, is not present in the Private Bank Index. The TOM dummy remains statistically insignificant at all traditional levels across CC (p=0.419), CO (p=0.160), and OC models (p=0.160). Even though the coefficient is positive, the lack of significance indicates that Private Bank stocks do not systematically generate higher returns around the month-end or start of the month.

The Turn-of-the-Year effect is also absent in the Private Bank Index. The TOY dummy is insignificant in CC (p=0.741), CO (p=0.923), and OC (p=0.745) models. This suggests that the end-of-year or beginning-of-year periods do not produce any abnormal returns. Thus, the Private Bank Index does not exhibit a turn-of-the-year seasonal pattern.

Finally, the week-of-the-month analysis also reveals no significant anomalies. None of the week dummies (2nd, 3rd, 4th, or 5th week) are significant in the CC, CO, or OC regressions, with p-values consistently above the 10% level. The F-statistics for week-of-the-month models are also insignificant ($p > 0.18$ across models). This indicates that returns do not systematically differ across the four or five weeks of the month in the Private Bank Index.

For the PSU Bank Index, the day-of-the-week regressions reveal no significant weekday effect across all three return measures. In the close-to-close (CC) model, none of the weekday dummies Tuesday, Wednesday, Thursday, or Friday are significant even at the 10% level, and the overall model is insignificant (F-stat $p = 0.5956$). Similarly, in the open-to-close (CO) and close-to-open (OC) regressions, all weekday coefficients remain statistically insignificant. Although the OC constant is significant, indicating a negative average overnight return, this is not tied to any specific weekday. Thus, the PSU Bank Index exhibits no day-of-the-week anomaly, suggesting weekday returns behave randomly without systematic patterns.

The month-of-the-year models also provide no evidence of monthly seasonality. In the CC, CO, and OC regressions, none of the months show statistical significance at the 10% level. October in the CC model approaches marginal significance ($p = 0.1089$) but does not cross the 10% threshold. Additionally, the F-statistics for all three models are insignificant, confirming that returns do not vary systematically across months. Thus, the PSU Bank Index does not exhibit a January effect, April effect, or any other monthly anomaly.

The half-year dummy (second half vs. first half of the year) is completely insignificant in all CC, CO, and OC regressions, with p-values far above 0.10. Even though the constants in CO and OC models are statistically significant, the half-year dummy itself does not contribute meaningfully to return variations. Therefore, the PSU Bank Index shows no half-year anomaly, and returns remain stable between January–June and July–December.

The half-month regressions similarly indicate no half-month anomaly. Neither in CC, CO, nor OC do the second-half-month dummies reach significance ($p > 0.29$ in all cases). This suggests that returns on PSU Bank stocks do not systematically increase or decrease in the second half of the month relative to the first.

A strong finding emerges in the turn-of-the-month analysis. In the CC model, the TOM dummy is positive and statistically significant at the 5% level ($p = 0.0304$), suggesting that PSU Bank returns are higher around the transition from one month to the next. The CO model also shows a marginally significant TOM effect at the 10% level ($p = 0.0990$), indicating that a portion of this return premium occurs during trading hours. The OC model shows a positive coefficient that is marginal at the 10% level ($p = 0.1083$) but falls just outside conventional significance. Overall, the evidence indicates a clear and consistent TOM anomaly, where PSU Bank stocks generate abnormal returns around month-end and month-start. The TOY dummy is insignificant in all models (CC, CO, OC), with p-values far above 0.10 (0.58, 0.94, 0.52). Thus, the PSU Bank Index does not exhibit a turn-of-the-year effect, meaning year-end or year-beginning periods do not yield abnormal returns.

The week-of-the-month regressions show notable patterns. In the CC model, the fourth week is significant at the 5% level ($p = 0.0308$), indicating that returns are comparatively lower in this week. The second week is weakly significant at the 10% level ($p = 0.0529$), also showing negative effects. In the CO model, both the second week ($p = 0.0121$) and third week ($p = 0.0299$) are statistically significant at the 5% level, suggesting lower intraday returns during these weeks. The fourth and fifth weeks are insignificant in the CO model, while the OC model shows only a marginal effect for the fourth week at the 10% level ($p = 0.0786$). Overall, the PSU Bank Index exhibits a distinct week-of-the-month anomaly, with returns systematically declining in the 2nd, 3rd, and 4th weeks of the month.

The Realty sector displays no meaningful day-of-the-week effect, as none of the weekday coefficients are statistically significant across the close-to-close (CC), open-to-close (CO), or close-to-open (OC) models, and the F-statistics confirm that weekday returns do not jointly explain return variations. Similarly, the month-of-the-year effect is absent, with all monthly dummies across CC, CO, and OC models showing p-values well above 10%. Although August in the CO model approaches the 10% threshold ($p = 0.0892$), it still remains statistically insignificant. Thus, neither weekdays nor months systematically influence Realty sector returns.

The half-year effect also does not manifest in the Realty index, as the second-half-year dummy is insignificant in all three models. In contrast, the half-month effect shows partial evidence of seasonality. In the CC model, the second half of the month shows a near-significant negative impact at the 10% level ($p = 0.0851$), while in the OC model, the same dummy is significant at the 5% level ($p = 0.0449$), indicating that overnight returns tend to fall in the latter half of the month. However, the CO model does not support this pattern, suggesting that the half-month anomaly, while present, is confined primarily to the overnight return component.

A striking and robust pattern appears for the turn-of-the-month (TOM) effect, which is highly significant in both the CC and OC regressions. The CC model reveals a strong positive TOM effect ($p < 0.01$), and the OC model similarly shows a highly significant coefficient ($p < 0.01$), demonstrating that Realty stocks consistently generate excess returns around the month-end and month-beginning period. The CO model, however, shows no significance, indicating that most of this anomaly is captured overnight rather than during the trading day. In contrast, the turn-of-the-year (TOY) effect is not observed, as all TOY coefficients across models remain insignificant.

Finally, the week-of-the-month effect emerges as one of the most pronounced anomalies in the Realty sector. In the CC model, returns in the second ($p = 0.0398$), third ($p = 0.0038$), and fourth weeks ($p = 0.0004$) of the month are significantly negative, with the fourth week displaying the strongest decline. The OC model mirrors this pattern, with the third ($p = 0.0022$) and fourth weeks ($p = 0.0002$) showing highly significant negative overnight returns, and the second week approaching significance at the 10% level ($p = 0.0716$). The CO model, however, shows no weekly significance. Overall, the Realty index reveals substantial intra-month weakness during Weeks 2–4, particularly driven by overnight price adjustments.

The Nifty50 index exhibits mixed but statistically meaningful evidence of calendar anomalies across trading-day (CO), non-trading-day (OC), and close-to-close (CC) returns. The Augmented Dickey–Fuller test confirms that all return series are stationary at the 1% level, validating the regression framework and ensuring the absence of spurious results.

The day-of-the-week effect is clearly present, particularly on Wednesdays. In all three models CC, CO, and OC the Wednesday dummy is highly significant at the 1% level, indicating consistently higher returns compared to Mondays. Friday also shows weak evidence of positivity in the CC model ($p = 0.1022$), significant at the 10% level, while Tuesday and Thursday remain insignificant across return types. The joint significance (Prob(F) < 0.001 for CC and < 0.001 for CO) indicates that weekday returns differ systematically, confirming a strong mid-week pattern in Nifty50.

Month-of-the-year effects are generally absent in Nifty50. In the CC model, December stands out as the only significant month, with a positive coefficient ($p = 0.041$), indicating higher December returns at the 5% significance level. In the CO model, no months are significant, although August shows mild evidence of lower trading-day returns ($p = 0.0681$), significant at 10%. In the OC model, both April ($p = 0.0531$) and November ($p = 0.0809$) are marginally significant at 10%, while December is strongly positive at the 1% level ($p = 0.0104$). Despite a few month-specific effects, the overall F-tests show that months do not jointly explain variations in returns, indicating no robust monthly seasonality.

The half-year anomaly is absent in all models. Neither CC, CO, nor OC return regressions show significance for the second-half-year dummy (all $p > 0.30$). This suggests that market behavior does not shift structurally across the fiscal halves for the Nifty50.

The half-month effect is also absent, as the second-half-month dummy is insignificant across CC, CO, and OC regressions (all $p > 0.20$). This indicates that splitting the month into two halves does not produce systematic differences in Nifty50 returns.

A strong and consistent TOM effect is observed across all three return measures. The TOM coefficient is highly significant at the 1% level for CC ($p = 0.0002$) and OC returns ($p = 0.0014$), and at the 5% level for CO returns ($p = 0.0245$). All coefficients are positive, indicating that Nifty50 generates excess returns around the month-end and month-beginning period. This is one of the most robust anomalies documented for the index. The TOY effect is partially present. In the CC model, TOY is significant at the 10% level ($p = 0.0507$), suggesting slightly higher returns around the year-end. However, the effect is not supported in CO or OC returns ($p > 0.11$). Thus, year-turn anomalies exist but only modestly and primarily in close-to-close returns.

The Nifty50 shows strong and systematic week-of-the-month anomalies, especially pronounced in the later weeks. In the CC model, the second, third, and fourth weeks exhibit significant negative returns at the 1% and 5% levels, with the strongest declines in the third and fourth weeks (both $p = 0.0024$). The CO model shows significance for the second ($p = 0.0079$) and third weeks ($p = 0.0265$), and marginal significance for the fourth and fifth weeks ($p = 0.056$ and $p = 0.0769$). In the OC model, the third ($p = 0.0156$) and fourth weeks ($p = 0.0113$) show highly significant negative overnight returns, while the second week is borderline significant ($p = 0.0595$). The joint F-tests ($p = 0.0079$ for CC and $p = 0.0395$ for OC) confirm that week-of-the-month effects are economically meaningful and statistically strong.

Chapter 3

Calendar Anomalies In Size Based Indices

3.1 Introduction

This chapter outlines the research methodology, empirical results, and discussion pertaining to calendar anomalies in size-based indices of the Indian stock market. The analysis focuses on the Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250 indices to evaluate whether return patterns differ across large-cap, mid-cap, and small-cap segments. By assessing multiple calendar effects across size-based indices, this chapter sheds light on whether firm size influences the persistence or magnitude of seasonal anomalies, thereby contributing to a more nuanced understanding of market efficiency across different tiers of the equity market.

3.2 Research methodology of objective II

This objective examines the behaviour of size-based indices of the National Stock Exchange of India (NSE), with a specific focus on large-cap, mid-cap, and small-cap market segments. To operationalise size classification, the study employs three widely accepted benchmark indices that is the Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250. These indices collectively represent the performance of Indian companies differentiated by market capitalisation, where the Nifty 100 captures the largest and most liquid firms, the Nifty Midcap 150 reflects medium-sized growth-oriented companies, and the Nifty Smallcap 250 tracks emerging and relatively less liquid firms with small market capitalisation.

Daily closing price data for all three indices were obtained directly from the official NSE India website, ensuring the authenticity and reliability of the dataset. The period of study spans fourteen years, from 01 January 2011 to 31 December 2024, offering a sufficiently long time horizon. Using a long, continuous dataset allows the analysis to be more robust and sensitive to recurring seasonal patterns. The daily returns for each index were computed using the logarithmic return formula, which is standard in empirical financial research due to its statistical properties and suitability for time-series modelling. These return series form the basis for examining whether size-based portfolios exhibit differential behaviour in the presence of calendar anomalies.

Furthermore, the selection of size-segmented indices allows the study to evaluate whether anomalies manifest uniformly across market-cap tiers or whether smaller firms, often considered riskier and less efficient, display stronger or weaker seasonal effects relative to larger firms. This methodological design ensures that the analysis not only tests for the presence of calendar anomalies but also provides insights into how firm size influences anomaly persistence within the Indian equity market.

3.2.1 Dummy Variable Regression Framework for Calendar Anomalies

To estimate the presence of various calendar anomalies such as Day-of-the-Week, Month-of-the-Year, Turn-of-the-Month, Turn-of-the-Year, Half-Year, Half-Month, and Week-of-the-Month effects a dummy variable regression model was employed. The general form of the estimation model is:

$$R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_k D_{kt} + \varepsilon_t \tag{10}$$

Where:

R_t = daily return of the index (large-cap, mid-cap, or small-cap)

D_{kt}= dummy variables representing the specific anomaly under examination

β_k = differential return associated with the anomaly

ε_t = error term

Separate regressions were estimated for each anomaly and for each index, allowing comparison of anomaly intensity across size classes. The analytical design and econometric procedures employed in this objective replicate those applied in Objective 1, thereby preserving a coherent and uniform methodological structure across the study. Maintaining an identical framework across objectives enables direct comparability of anomaly behaviour. This uniformity ensures that observed variations arise from inherent index characteristics rather than differences in estimation techniques.

3.3 Results and Discussion

3.3.1 Calendar anomalies in size-based indices

Table 3.1: Significant calendar anomalies in Nifty 100, Nifty Midcap 150, and Nifty Smallcap 250

Index	Effect	Result	Sign
Nifty 100	DOW	Tue, Fri	Highest
	MOY	NS	-
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	NS	-
	WOM	4	Lowest
Midcap 150	DOW	Wed	Highest
	MOY	April	Highest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	NS	-
	WOM	2,3,4	Lowest
Smallcap 250	DOW	NS	-
	MOY	April, Oct	Highest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	Yes	Highest
	WOM	3,5	Lowest Highest

Note: 'NS' indicates statistically insignificant.

Table 3.1 exhibit the summary of **Annexure**. The stationarity check using the Augmented Dickey-Fuller test confirms that the Nifty 100 returns series is stationary at level, as indicated by a highly significant ADF statistic ($t = -57.80$, $p < 0.0001$), enabling reliable regression-based anomaly testing. The Day-of-the-Week regression reveals partial evidence of a weekday effect, with Tuesday returns being significantly higher than Monday ($\beta = 0.1254$, $p = 0.0263$). Although Friday also shows a positive and moderately strong coefficient ($\beta = 0.0944$, $p = 0.0956$), its significance is marginal, suggesting that the large-cap segment tends to exhibit mild early-week rebounds and end-week optimism, but not strong enough to classify as a persistent anomaly across the sample period. No meaningful Month-of-the-Year effects are observed, as none of the monthly dummies are statistically significant and the model's overall F-statistic is insignificant ($p = 0.8858$), indicating the absence of seasonal monthly patterns in large-cap returns. Similarly, both the Half-Year effect ($\beta = 0.0135$, $p = 0.7051$) and the Half-Month effect ($\beta = -0.0204$, $p = 0.5673$) are statistically insignificant, suggesting that broader semi-annual and intra-month cycles do not influence Nifty 100 performance.

In contrast, a strong and statistically significant Turn-of-the-Month effect is detected, with returns increasing sharply during the last and first few days of each month ($\beta = 0.1096$, $p = 0.0156$). This finding reinforces the role of systematic liquidity inflows such as SIP contributions, fund rebalancing, or salary-driven investments that tend to cluster around month-end and month-beginning, benefiting large-cap stocks where institutional participation is highest. The Turn-of-the-Year coefficient is positive but insignificant ($\beta = 0.0152$, $p = 0.8385$), indicating that the Nifty 100 does not exhibit a year-end rally or window-dressing pattern. Finally, the Week-of-the-Month results show weak and statistically insignificant intra-month patterns, although the coefficient for the fourth week ($\beta = –0.1019$, $p = 0.08$) is close to significance, hinting at mild late-month profit-booking in large-cap stocks. Overall, among all tested anomalies, Turn-of-the-Month emerges as the only strong and consistent calendar effect for Nifty 100, while other anomalies DOW, MOY, HY, HM, TOY, and WOM show no robust or persistent statistical significance.

The MIDCAP 150 index demonstrates selective but meaningful calendar anomalies over the 2011–2024 period. The Day-of-the-Week effect appears partially present, with Wednesday showing the highest positive return ($\beta = 0.1096$, $p = 0.0828$), although only marginally significant at the 10% level, while other weekdays remain statistically insignificant, indicating weak evidence of systematic weekday patterns. The Month-of-the-Year effect is clearer for April, which records a noticeably high positive return ($\beta = 0.1768$, $p = 0.0752$), again significant at the 10% threshold, suggesting that mid-cap stocks tend to outperform during this month, while all other months remain statistically insignificant. At the broader temporal level, no Half-Year (HY) or Half-Month (HM) effects are detected, as both second-half-of-year and second-half-of-month dummy variables return insignificant coefficients with $p > 0.16$, showing no systematic periodicity across these intervals.

A strong and statistically robust anomaly emerges through the Turn-of-the-Month (TOM) effect, where returns significantly increase during the beginning and end of each month ($\beta = 0.2560$, $p < 0.01$), marking TOM as the most prominent anomaly in the MIDCAP 150 index. In contrast, the Turn-of-the-Year effect (TOY) shows no meaningful influence ($p = 0.3746$). However, the Week-of-the-Month (WOM) effect is strongly supported, as returns in the second, third, and fourth weeks exhibit significantly negative coefficients Second Week ($\beta = -0.1433$, $p = 0.0268$), Third Week ($\beta = -0.1899$, $p = 0.0035$), and Fourth Week ($\beta = -0.2257$, $p = 0.0005$). This consistent decline indicates that mid-cap stocks tend to underperform substantially during the middle and later weeks of each month, while the fifth week shows no pattern due to fewer observations. Taken together, the Midcap 150 displays a pattern where returns peak at the turn of the month and during April, while performance weakens during the mid-month weeks, highlighting a mix of both return-enhancing and return-suppressing anomalies within the size-based mid-cap segment of the Indian equity market.

The Smallcap 250 index exhibits a distinct pattern of calendar anomalies, though these effects are selective rather than widespread. The Day-of-the-Week effect is absent, as none of the weekday coefficients are statistically significant (all $p > 0.26$), indicating no systematic weekday return pattern within the small-cap segment. In contrast, the Month-of-the-Year anomaly shows partial validity. April emerges as a statistically significant high-return month ($\beta = 0.2321$, $p = 0.0379$), indicating strong positive performance at the 5% significance level. October also displays marginally elevated returns ($\beta = 0.1899$, $p = 0.0846$), significant at the 10% level, while December reflects a similar tendency though not at conventional significance ($\beta = 0.1710$, $p = 0.1148$). These results suggest that small-cap stocks tend to perform better during specific months, particularly April, with supporting evidence in October.

No meaningful Half-Year or Half-Month effects are detected, as both second half year and second half month variables return statistically insignificant results ($p = 0.38$ and $p = 0.49$ respectively), indicating that broad periodic patterns across the year or month do not drive small-cap returns. However, the Turn-of-the-Month effect is strong and highly significant ($\beta = 0.1996$, $p = 0.0005$), marking TOM as one of the most robust anomalies in the SMALLCAP 250. Similarly, the Turn-of-the-Year effect is statistically significant at the

1% level ($\beta = 0.2472$, $p = 0.0086$), suggesting that small-cap returns exhibit notable increases around the transition from December to January.

The Week-of-the-Month effect is partially observed. Third Week returns are significantly negative ($\beta = –0.2004$, $p = 0.0061$), indicating systematic underperformance during this period. Conversely, the Fifth Week shows strong positive returns ($\beta = 0.2229$, $p = 0.0059$), implying substantial gains whenever an additional trading week occurs in a month. The second and fourth weeks do not show significant effects. Overall, the Smallcap 250 index displays a combination of positive seasonal anomalies particularly in April, the turn-of-the-month, and the turn-of-the-year alongside a pronounced mid-month dip and an end-month uplift when a fifth week is present. These patterns highlight behavioral and structural influences that are more prominent in the small-cap segment compared to large-cap indices.

Chapter 4

Calendar Anomalies In Select Emerging Markets

4.1 Introduction

This chapter investigates the presence of calendar anomalies in select emerging market stock indices, while also examining volatility dynamics through the leverage effect. Using daily data from seven emerging markets, the analysis integrates dummy variable regression models and TGARCH specifications to capture both return based anomalies and asymmetric volatility responses, offering a comprehensive understanding of market behaviour across diverse economic environments.

4.2 Research methodology of objective III

In this objective the study investigates the presence of calendar anomalies in select emerging market stock indices, alongside the influence of the volatility leverage effect. Daily closing prices of seven emerging market indices, such as Brazil (Bovespa), China (Shanghai Composite Index), Indonesia (Jakarta Stock Exchange), Mexico (BMV IPC), India (Nifty50), Russia (MOEX), and Turkey (BIST 100). The dataset consists of daily stock index returns for each market, covering the period from 1st January, 2001, to 31st December, 2024. To test for the existence of seven calendar anomalies namely Day-of-the-Week (DOW), Week-of-the-Month (WOM), Half-Monthly (HM), Month-of-the-Year (MOY), Half-Yearly (HY), Turn-of-the-Year (TOY), and Turn-of-the-Month (TOM) effects the study employs a Dummy Variable Regression model, which allows identification of return patterns associated with specific calendar periods. Checking for heteroskedasticity in the residuals is essential to account for the time-varying volatility often observed in stock return series. To test for the presence of an ARCH effect, the ARCH LM test is applied (Jain, Mittal, & Choudhary, 2022), with results evaluated at a 5% significance level. The null hypothesis states that no ARCH effect exists in the log return series (Kumar & Jawa, 2017). Furthermore, To account for the leverage effect in volatility dynamics, the study employs the GJR framework that allows negative shocks to exert a larger impact on conditional variance (Glosten, Jagannathan, & Runkle, 1993). This model accounts for conditional heteroskedasticity and the differential impact of good and bad news on market volatility. This dual approach provides a comprehensive examination of both return anomalies and volatility behaviour, offering robust insights into market efficiency and behavioural tendencies of these emerging financial markets. The TGARCH model is particularly effective in capturing the leverage effect, a phenomenon where negative shocks have a greater impact on volatility than positive shocks of equal magnitude (Zakoian, 1994). EViews estimates the Threshold GARCH (TGARCH) model using the Glosten-Jagannathan-Runkle (GJR) specification. In this framework, the conditional variance depends on past shocks, but negative shocks have an additional effect captured through an indicator term. The estimated variance equation takes the form:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}<0\}} + \beta h_{t-1} \tag{11}$$

where γ measures the asymmetric or leverage effect. A positive and significant γ indicates that negative shocks increase volatility more than positive shocks of the same magnitude. In the TGARCH (GJR-GARCH) model, ω captures long-run volatility, α measures the immediate impact of past shocks, β represents the persistence of volatility, and γ captures the asymmetric effect whereby negative shocks increase volatility more than positive shocks. The indicator function ensures that the asymmetric term contributes to volatility only when a negative return occurs.

4.3 Results and Discussion

4.3.1 Calendar anomalies in select emerging markets

Table 4.1: Significant calendar anomalies in select emerging markets

Index	Effect	Result	Sign
Brazil (Bovespa)	DOW	Wed	Highest
	MOY	May, June	Lowest
	HY	Yes	Highest
	HM	NS	-
	TOM	Yes	Highest
	TOY	Yes	Highest
	WOM	2,3,4,5	Lowest
China	DOW	Thur	Lowest

(Shanghai Composite Index)	MOY	June, August, Sept	Lowest
	HY	NS	-
	HM	Yes	Lowest
	TOM	Yes	Highest
	TOY	NS	-
	WOM	Yes	Lowest
India (Nifty50)	DOW	NS	-
	MOY	May	Highest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	NS	-
	WOM	NS	-
Indonesia (Jakarta Stock Exchange)	DOW	All	Highest
	MOY	NS	-
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	Yes	Highest
	WOM	2,4,5	Lowest
Mexico (BMV IPC)	DOW	NS	-
	MOY	Feb	Lowest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	Yes	Highest
	WOM	2,3,4,5	Lowest
Russia (MOEX)	DOW	ALL	Lowest
	MOY	March, May	Lowest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	Yes	Highest
	WOM	2,3,4,5	Lowest
Turkey (BIST 100)	DOW	Tue	Lowest
	MOY	Feb, Mar, May, June, August	Lowest
	HY	NS	-
	HM	NS	-
	TOM	Yes	Highest
	TOY	NS	-
	WOM	NS	-

Note: ‘NS’ indicates statistically insignificant.

The Augmented Dickey–Fuller (ADF) test confirms that the return series of the Bovespa index is stationary, as indicated by the highly significant test statistic ($t = –79.80$, $p < 0.01$), allowing for robust regression and volatility modelling. The Day-of-the-Week regression reveals limited evidence of weekday seasonality, with only Wednesday showing a statistically significant positive return ($\beta = 0.103$, $p = 0.048$), suggesting a mild mid-week effect, while all other weekdays remain insignificant. Month-of-the-Year results indicate the absence of broad monthly anomalies, although June exhibits a statistically significant negative return ($\beta = –0.1668$, $p = 0.044$), and May is marginally significant at the 10% level ($\beta = –0.1447$, $p = 0.0666$), reflecting some month-specific weakness. A notable calendar effect emerges in the Half-Yearly model, where the second half of the year shows significantly higher returns ($\beta = 0.0840$, $p = 0.014$), while no evidence supports the Half-Month effect. Strong support is observed for the Turn-of-the-Month (TOM) anomaly, with a positive and highly significant coefficient ($\beta = 0.1486$, $p = 0.0005$), indicating that returns tend to rise around month-end. The Turn-of-the-Year (TOY) effect is also present ($\beta = 0.1834$, $p = 0.014$), suggesting abnormally high returns around the year-end transition. The Week-of-the-Month (WOM) pattern is particularly pronounced in Brazil: all weeks except the first show significant negative returns second ($\beta = –0.217$, $p = 0.0001$), third ($\beta = –0.126$, $p = 0.0215$), fourth ($\beta = –0.1909$, $p = 0.0005$), and fifth week ($\beta = –0.2056$, $p = 0.0008$) indicating a strong declining trend as the month progresses.

The ARCH LM test consistently rejects the null hypothesis ($p < 0.05$), confirming the presence of heteroskedasticity and justifying the use of a TGARCH(1,1) model. The variance equation shows a large and significant GARCH parameter ($\beta \approx 0.91$, $p < 0.01$), indicating high volatility persistence in the Brazilian market, meaning shocks to volatility dissipate slowly. The ARCH term is positive and significant ($\alpha \approx 0.023–0.024$, $p < 0.01$), suggesting that recent market shocks increase current volatility. Most importantly, the leverage term ($\gamma \approx 0.087–0.089$, $p < 0.01$) is strongly significant, confirming the presence of asymmetric volatility: negative news (bad returns) leads to disproportionately higher volatility than positive news of the same magnitude. Overall, the Brazilian stock market exhibits selective but meaningful calendar anomalies particularly mid-week, mid-year, TOM, TOY, and week-of-the-month effects combined with persistent and asymmetric volatility characteristic of emerging markets.

The results for the Shanghai Composite Index reveal several notable calendar anomalies, though the strength of these anomalies is mixed across different temporal dimensions. Starting with the day-of-the-week effect, only Thursday shows a statistically significant result, with a negative return of −0.1174 ($p = 0.0045$). This indicates that Thursdays tend to experience lower returns relative to Monday, suggesting a mild but consistent weekday anomaly in the Chinese market. The other weekdays that is Tuesday, Wednesday, and Friday do not display significant effects, implying that daily return patterns are otherwise relatively efficient.

Moving to the month-of-the-year effect, all monthly coefficients are negative, though none are statistically significant at the 5% level. Months such as June (−0.1165, $p = 0.0763$), August (−0.1127, $p = 0.0987$), and September (−0.1024, $p = 0.091$) show marginal significance at the 10% threshold, hinting at weaker performance in late summer and early autumn. However, the absence of strong significance across months suggests that the Shanghai Composite does not exhibit a robust, predictable monthly anomaly, aligning more with market efficiency in this dimension.

The half-year effect also appears weak, as the coefficient for the second half of the year is negative (−0.0169) but statistically insignificant ($p = 0.5345$). This reinforces the view that semi-annual seasonal patterns do not meaningfully influence returns in the Chinese market. In contrast, the half-month effect is quite strong: the second half of the month shows a significant negative return of −0.0877 ($p = 0.0015$), indicating that returns tend to decline substantially during the latter half of each month. This pattern suggests a systematic intra-month return cycle that investors could exploit.

A very strong anomaly emerges in the turn-of-the-month period. The TOM coefficient is large and positive (0.2135) and highly significant ($p < 0.001$), indicating that returns increase sharply around the turn-of-the-month window. This is one of the strongest observed anomalies for China, consistent with liquidity flows, salary cycles, and institutional rebalancing effects. On the other hand, the turn-of-the-year effect does not appear meaningful, with a positive but insignificant coefficient of 0.0887 ($p = 0.1406$), meaning the Chinese market does not display a traditional January-style seasonality.

Finally, the week-of-the-month effect shows several significant negative coefficients. The second week (−0.0891, $p = 0.0475$), third week (−0.1739, $p < 0.001$), fourth week (−0.1499, $p < 0.001$), and fifth week (−0.1471, $p = 0.0043$) all show substantial negative returns relative to the first week. This pattern indicates that returns tend to concentrate in the first week of each month, with consistent declines in subsequent weeks. When considered together with the strong TOM effect, this suggests that Chinese market gains are heavily clustered near the beginning of each month, followed by corrections or weaker momentum afterward.

The results for India's Nifty50 index show a consistent pattern of stationarity in the return series, as indicated by the highly significant ADF statistic ($t = –73.41$, $p < 0.01$), confirming that the data is suitable for modelling anomalies. The significant ARCH LM test in the unconditional model establishes the presence of volatility clustering; however, once the TGARCH specification is applied, the ARCH LM probabilities become insignificant ($p > 0.80$), indicating that the TGARCH(1,1) model successfully captures the conditional heteroskedasticity. The variance equation further reveals a strong and statistically significant leverage effect, as negative shocks have a larger impact on volatility than positive shocks, consistent with the asymmetric behaviour documented in emerging markets.

Turning to the anomaly estimates, no Day-of-the-Week effect is observed in the Nifty50, as none of the weekday dummies show significance, even at the 10% level. This suggests that daily returns are evenly distributed across trading days with no systematic Monday or weekend-related patterns. Similarly, the Month-of-the-Year effect is broadly absent. Although May shows a mildly positive return ($\beta = 0.0900$, $p \approx 0.079$), this significance is only at the 10% level and remains isolated, with all other monthly coefficients insignificant. Thus, there is no stable monthly seasonal pattern in India's equity market.

The Half-Year effect also does not manifest, as the second half of the year dummy carries no significance, indicating returns do not structurally differ between January–June and July–December periods. The Half-Month anomaly behaves similarly, with the second-half-of-month coefficient remaining insignificant, suggesting that returns are not concentrated around the early or late segments of the month.

A notable exception appears in the Turn-of-the-Month (TOM) effect. The TOM coefficient is strongly positive and significant ($\beta = 0.0890$, $p < 0.01$), indicating that returns during the transition window between months are consistently higher. This is one of the few statistically robust anomalies in the Indian market. In contrast, the Turn-of-the-Year (TOY) effect is absent, as the TOY coefficient is small and insignificant, implying no unusual return behaviour around the New Year.

Finally, the Week-of-the-Month effect also fails to show significance in the Nifty50. Although second, third, and fourth week coefficients are negative, none reach the 10% significance level, confirming that weekly position within the month does not materially influence returns in India.

The return series of the Jakarta Stock Exchange displays strong evidence of stationarity, as confirmed by the Augmented Dickey–Fuller statistic ($t = –69.65$, $p < 0.01$), indicating that the data is suitable for modelling return behaviours and volatility dynamics. The initial ARCH LM test reveals significant heteroskedasticity ($p = 0.0000$), validating the need for a conditional volatility model. Once the TGARCH(1,1) specification is applied, the ARCH LM probabilities rise above 0.35, signalling that the model adequately captures time-varying volatility. The variance equation shows high volatility persistence ($\beta \approx 0.86$, $p < 0.01$) along with a significant asymmetric term ($\gamma \approx 0.07$, $p < 0.01$), implying a strong leverage effect, where negative shocks increase volatility more than positive shocks of similar magnitude a characteristic commonly observed in emerging equity markets.

Turning to the seasonal anomalies, Indonesia exhibits a clear and strong Day-of-the-Week (DOW) effect. Tuesday ($\beta = 0.166$, $p < 0.01$), Wednesday ($\beta = 0.234$, $p < 0.01$), Thursday ($\beta = 0.150$, $p < 0.01$), and Friday ($\beta = 0.193$, $p < 0.01$) all show significantly higher returns compared to Monday. Among these, Wednesday provides the highest abnormal return, indicating mid-week return clustering in the Indonesian market. This makes Indonesia one of the few emerging markets where the DOW effect remains statistically robust even after adjusting for volatility through TGARCH.

In contrast, Month-of-the-Year (MOY) effects are largely absent. None of the monthly dummies exhibit significance at the 10% level, although July shows a near-significant positive tendency ($\beta = 0.089$, $p \approx 0.128$). This suggests that Indonesian equity returns do not systematically vary across calendar months, in contrast to markets where January or April effects are common.

The Half-Year (HY) effect is also not present, with the second-half-year coefficient being insignificant ($\beta = 0.0066$, $p \approx 0.79$). Similarly, the Half-Month (HM) effect shows no evidence of return clustering, as the second-half-of-month dummy remains insignificant ($\beta = -0.0007$, $p \approx 0.98$). These results suggest that Indonesian returns are not influenced by the broader or narrower structural divisions within the month or year.

The Turn-of-the-Month (TOM) effect is observed, with a statistically significant positive coefficient ($\beta = 0.0554$, $p \approx 0.038$), indicating higher returns during the transition window between two months. This aligns with global evidence that transaction-timing and institutional fund flows often generate end-of-month return premiums.

The Turn-of-the-Year (TOY) effect appears marginal. The TOY dummy is positive and significant at the 10% level ($\beta = 0.0884$, $p \approx 0.098$), suggesting mildly elevated returns around the New Year, though not strong enough to be considered a robust anomaly at conventional (5%) significance.

A notable finding emerges in the Week-of-the-Month (WOM) anomaly. The second week ($\beta = -0.122$, $p < 0.01$), fourth week ($\beta = -0.079$, $p < 0.05$), and fifth week ($\beta = -0.105$, $p < 0.05$) all exhibit significantly lower returns, while the third week remains insignificant. The concentration of negative returns in weeks 2, 4, and 5 suggests a recurring intra-month pattern of weak performance, making WOM one of the strongest calendar anomalies in Indonesia alongside the DOW and TOM effects.

The unit root results confirm that the return series of the Mexican BMV IPC index is stationary, as indicated by the highly significant ADF test statistic ($t = -72.49$, $p = 0.0001$). The initial ARCH test shows strong evidence of heteroskedasticity, justifying the use of TGARCH modelling. Across all models, the variance equation demonstrates a statistically significant leverage effect: the coefficient for negative shocks (RESID(–1)^2 × negative) is consistently large and highly significant (e.g., 0.1059, $p < 0.001$), implying that bad news increases volatility more than good news, a characteristic frequently observed in emerging markets. The GARCH(1) term remains dominant (≈0.91), indicating persistent long-term volatility.

Examining the Day-of-the-Week (DOW) anomaly, none of the weekday coefficients are statistically significant, suggesting the Mexican market does not exhibit any systematic weekday return pattern. The Month-of-the-Year (MOY) effect is similarly weak, with only February showing a significant negative return ($\beta = -0.1156$, $p = 0.0446$). This indicates that returns tend to be lower in February, while all other months show no abnormal performance. The Half-Yearly (HY) and Half-Month (HM) effects are absent, as their coefficients are statistically insignificant implying no systematic difference between first/second halves of the year or month.

In contrast, a strong Turn-of-the-Month (TOM) effect is present. The TOM dummy is highly significant ($\beta = 0.0784$, $p = 0.0045$), showing that returns around the transition between months are substantially higher in Mexico. Even more prominent is the Turn-of-the-Year (TOY) effect, which reveals a significant positive coefficient ($\beta = 0.1205$, $p = 0.0098$), indicating that the Mexican market experiences elevated returns during the year-end and New Year transition, consistent with investor behavior such as portfolio rebalancing or tax-driven timing effects.

The Week-of-the-Month (WOM) anomaly is also strongly evident. The second, third, fourth, and fifth weeks show significant negative coefficients (e.g., second week $\beta = -0.1599$, $p < 0.001$; fifth week $\beta = -0.1161$, $p = 0.0027$), implying returns tend to be lowest during mid-to-late weeks of the month, with the first week serving as the implicit baseline. These results indicate that Mexico exhibits one of the strongest WOM patterns among emerging markets in your dataset, with the most pronounced negative anomalies concentrated in weeks 2–5.

The Augmented Dickey–Fuller test confirms that the Russian MOEX return series is stationary, with a highly significant ADF statistic ($t = -77.26$, $p = 0.0001$), making it suitable for regression modelling. The initial ARCH test shows strong heteroskedasticity, which justifies the application of the TGARCH model for volatility analysis. Across all specifications, the variance equation reveals a clear and statistically significant leverage effect: negative shocks (RESID(–1)^2 × negative) consistently increase volatility more intensely than positive shocks of the same magnitude. Moreover, the GARCH(1) term is extremely high (≈0.88), indicating highly persistent volatility a common characteristic of markets influenced by geopolitical risk and macroeconomic instability, such as Russia.

Turning to the Day-of-the-Week (DOW) anomaly, the results show partial evidence of weekday effects. Returns on Tuesday ($\beta = -0.0954$, $p = 0.0381$) and Thursday ($\beta = -0.1347$, $p = 0.0013$) are significantly negative, indicating that these two days tend to deliver lower returns relative to Monday. Wednesday and Friday coefficients are negative but insignificant, suggesting that the DOW effect in Russia is present but selective, with persistent weakness primarily on Tuesdays and Thursdays.

For the Month-of-the-Year (MOY) effect, the results indicate recurring negative return patterns across several months, although only March ($\beta = -0.1536$, $p = 0.0415$) and May ($\beta = -0.1675$, $p = 0.0277$) show statistically significant underperformance. The remaining months exhibit negative coefficients but are not significant at the 5% level, suggesting that although the MOEX tends to produce weaker returns during several months of the year, only March and May demonstrate consistent, statistically supported seasonality. The Half-Yearly (HY) and Half-Month (HM) effects do not appear in the Russian market. Both the second-half-year and second-half-month coefficients are negative but insignificant ($p > 0.20$), indicating that MOEX returns are not systematically different across broader time partitions such as halves of the year or month. In contrast, the Turn-of-the-Month (TOM) effect is strongly significant. The TOM coefficient is large and positive ($\beta = 0.1562$, $p < 0.001$), showing that returns increase materially during the transition between consecutive months. This suggests heightened trading volume, portfolio adjustments, or book-closing effects around month-ends. A similar pattern emerges for the Turn-of-the-Year (TOY) effect, where returns exhibit a statistically significant and positive jump at the start of the new year ($\beta = 0.1815$, $p = 0.0007$). This strong TOY effect reflects common year-end and new-year phenomena such as tax-motivated trading, institutional rebalancing, and renewed investor optimism.

The Week-of-the-Month (WOM) anomaly is one of the most pronounced in the Russian market. All weekly dummies second, third, fourth, and fifth weeks show significant negative coefficients (e.g., second week $\beta = -0.1094$, $p = 0.0145$; third week $\beta = -0.1628$, $p = 0.0008$; fourth week $\beta = -0.1174$, $p = 0.0027$; fifth week $\beta = -0.1385$, $p = 0.0106$). This reveals that returns are systematically highest in the first week of the month, with sharp declines in all subsequent weeks. Such a strong and consistent WOM structure indicates predictable monthly cyclical patterns in trading and liquidity within the MOEX.

For the Turkish equity market, the BIST 100 index displays return characteristics that are stationary, as confirmed by the ADF test ($t = –77.23$, $p < 0.01$), indicating that the return series does not suffer from unit root problems. The initial ARCH LM test strongly signals the presence of heteroskedasticity ($p = 0.00$), which justifies the use of a TGARCH(1,1) specification to account for time-varying and asymmetric volatility, and the variance equation confirms a significant leverage effect, as negative shocks (bad news) increase volatility more sharply than positive shocks. Examining the Day-of-the-Week effect, all weekday dummy coefficients are statistically insignificant at the 5% level, indicating no evidence of systematic weekday return patterns in the Turkish market. This suggests that investors do not earn abnormal returns based on trading days. In contrast, the Month-of-the-Year analysis reveals short-lived seasonal weakness, with February ($\beta = –0.194$, $p = 0.039$) and May ($\beta = –0.190$, $p = 0.022$) showing significantly negative returns. Other months, although mostly negative, are not statistically significant, implying that Turkey experiences mild seasonal downturns but lacks a strong, consistent MOY anomaly.

The Half-Yearly and Half-Monthly effects appear absent, as both second-half-of-year and second-half-of-month coefficients are statistically insignificant, indicating stable return behaviour across intra-year and intra-month segments. A clear anomaly emerges under the Turn-of-the-Month effect: the TOM dummy is positive and significant ($\beta = 0.0964$, $p = 0.045$), showing that the Turkish market exhibits higher returns at the beginning or end of the month, a finding consistent with liquidity-related trading behaviours. Conversely, the Turn-of-the-Year (TOY) effect is not significant ($p = 0.141$), suggesting that January-related seasonality is absent in BIST 100. For the Week-of-the-Month effect, none of the weekly dummies (2^{nd}, 3^{rd}, 4^{th}, 5^{th} weeks) are statistically meaningful, further confirming the absence of WOM-based patterns. Across all models, diagnostic tests after TGARCH estimation show no residual ARCH effects, confirming that the conditional variance specification is appropriate.

Chapter 5
Calendar Anomalies In Foreign Exchange Returns

5.1 Introduction

This chapter examines the existence of calendar anomalies in foreign exchange returns, focusing on four major currencies such as the US Dollar, Euro, Pound Sterling, and Japanese Yen. Using daily exchange rate data, the analysis employs dummy variable regression models to identify systematic return patterns, supplemented by sub-period analysis to understand how anomalies evolve across different macroeconomic phases.

5.2 Research methodology of objective IV

To achieve this objective, the study investigates the presence of calendar anomalies in foreign exchange rate, focusing on the US Dollar, Euro, Pound Sterling and Japanese Yen currency. Daily exchange rate data is collected over an extensive period of 24 years (1st January, 2001, to 31st December, 2024) from the Reserve Bank of India website. Daily returns are computed using logarithmic returns to accurately capture percentage changes in exchange rates. Regression analysis with dummy variables representing different calendar periods is conducted to test for the statistical significance of the anomalies. Finally, the overall study period from 2001 to 2024 was segmented into four sub-periods such as Pre-Crisis (2001-2006), Post-Crisis Recovery (2009-2014), Reform & Stabilization (2015-2019), and Post-Pandemic (2021-2024) to capture the evolution of calendar anomalies across distinct market and economic regimes. The first phase (2001-2006) represents the pre-global financial crisis era characterized by liberalization and steady market expansion, while the second phase (2009-2014) reflects post-crisis recovery and structural adjustment in both global and Indian markets. The third period (2015-2019) corresponds to a reform-driven and relatively stable growth phase, influenced by domestic policy changes such as GST implementation and demonetization. The final phase (2021-2024) covers the post-pandemic recovery, marked by digital acceleration and renewed volatility in global capital flows. The years 2007-2008 and 2020 were excluded intentionally, as they represent extreme market disruptions such as the global financial crisis and the COVID-19 shock respectively that could distort normal return behaviour. This clustering approach not only aligns with major macro-financial transitions but also ensures balanced sub-period lengths for robust statistical analysis and meaningful comparison of anomaly persistence over time.

5.3 Results and Discussion

5.3.1 Calendar anomalies in foreign exchange returns

Table 5.1 Significant calendar anomalies in USD/INR returns

USD/INR								
Period		**DOW**	**MOY**	**HY**	**HM**	**TOM**	**TOY**	**WOM**
Full (2001-2024)	Result	Tue	May, August, Nov	NS	NS	Yes	NS	2,3,4
	Sign	Highest	Highest			Lowest		Highest
2001-2006	Result	Tue	April, May	NS	NS	Yes	NS	2,3
	Sign	Highest	Highest			Lowest		Highest
2009-2014	Result	Tue	August, Nov	NS	NS	Yes	NS	3
	Sign	Highest	Highest			Lowest		Highest
2015-2019	Result	Fri	March, August	NS	NS	Yes	NS	NS
	Sign	Lowest	Lowest; Highest			Lowest		
2021-2024	Result	NS	NS	NS	NS	NS	NS	NS
	Sign	-	-	-	-	-	-	-

Note: ‘NS’ indicates statistically insignificant.

The empirical analysis of U.S. dollar returns reveals a structured yet evolving pattern of calendar-based inefficiencies across the study period. Prior to estimating the anomaly regressions, the Augmented Dickey–Fuller test confirms the stationarity of the return series, with an ADF statistic of –36.03 ($p = 0.0000$), enabling reliable inference free from non-stationary distortions. Within the spectrum of seasonal effects, the Day-of-the-Week (DOW) anomaly presents the most consistent evidence, led by a persistent and statistically significant Tuesday effect. For the full sample, Tuesday produces a positive and precisely estimated return of 0.000648 ($p = 0.0001$), and this pattern remains robust during 2001-2006 and 2009-2014, with coefficients of 0.000456 ($p = 0.0096$) and 0.00145 ($p = 0.0026$) respectively. The absence of significance after 2015, along with a brief negative Friday effect observed during 2015-2019 (–0.000691; p = 0.021), suggests that weekday anomalies once prominent have diminished in the last decade, consistent with the growing informational efficiency of currency markets.

The Month-of-the-Year effect further highlights pockets of seasonal regularities. Across the full sample, the U.S. dollar shows statistically elevated returns in May (0.000610; p = 0.0155) and August (0.000748; p = 0.0031), with November exhibiting marginal significance. Sub-period analyses reinforce these trends: May is significant during 2001-2006, while August emerges as a strong seasonal month during both 2009-2014 and 2015-2019. These patterns point to recurrent mid-year and late-summer strength in the U.S. dollar, although the effect is not uniformly persistent across all decades, reflecting the episodic nature of currency market seasonality.

Among all anomalies, the Turn-of-the-Month (TOM) effect stands out as the most distinct and counterintuitive. Unlike equity markets, where TOM returns are typically positive, the U.S. dollar exhibits a consistently negative TOM premium. In the full sample, the TOM coefficient is significantly negative (–0.000477; p = 0.0003), with even stronger effects in earlier periods particularly 2001-2006 (–0.000346; p = 0.0133) and 2009–2014 (–0.001117; p = 0.0036). This indicates that the dollar tends to weaken around month-end transitions, perhaps reflecting systematic liquidity adjustments or cross-border settlement timing. However, this anomaly dissipates after 2015, aligning with the broader pattern of weakening seasonal effects.

In contrast, the Turn-of-the-Year (TOY) anomaly shows no statistically meaningful behaviour across the full sample or any sub-period, suggesting that year-end currency positioning does not generate a predictable return premium. Similarly, both the Half-Month and Half-Year anomalies remain uniformly insignificant throughout the study period, indicating that returns do not systematically vary between the first and second halves of months or years.

Finally, the Week-of-the-Month anomaly uncovers an additional dimension of mid-month seasonality. For the full sample, returns are significantly higher during the Second Week (0.000447; p = 0.0084), Third Week (0.000485; p = 0.0046), and Fourth Week (0.000347; p = 0.042), implying a recurring concentration of positive performance toward the middle of each month. However, these effects are far weaker and often statistically absent in sub-period analyses, especially in the post-2015 decade, once again reflecting the diminishing role of calendar-based inefficiencies over time.

Table 5.2: Significant calendar anomalies in EUR/INR returns

EUR/INR								
Period		**DOW**	**MOY**	**HY**	**HM**	**TOM**	**TOY**	**WOM**
Full (2001-2024)	Result	Tue, Wed, Thur	April, May, June, July, August, Nov, Dec	NS	NS	Yes	NS	2,3
	Sign	Highest	Highest			Lowest		Highest
2001-2006	Result	NS	April, May	NS	NS	NS	NS	NS
	Sign		Highest					
2009-2014	Result	Tue, Wed, Thur	April, June, August	NS	NS	Yes	NS	2,3,4,5,
	Sign	Highest	Highest			Lowest		Highest
2015-2019	Result	NS	August	NS	NS	NS	NS	NS
	Sign		Highest					
2021-2024	Result	Thur	NS	NS	NS	NS	NS	NS
	Sign	Highest						

Note: 'NS' indicates statistically insignificant.

The analysis of EURO-denominated daily returns begins with a stationarity check using the Augmented Dickey–Fuller (ADF) test. The test statistic of –76.35 (p = 0.0001) decisively rejects the null hypothesis of a unit root, indicating that RETURNS_EURO is stationary and suitable for regression-based anomaly testing.

The full-sample regression (2001-2024) indicates a statistically significant Day-of-the-Week effect, largely concentrated in the mid-week. Tuesday yields a positive and significant return of 0.000829 (p = 0.0009), followed by Wednesday at 0.000654 (p = 0.0085). Thursday is marginally significant at the 10% level, while Friday shows no abnormal return. This suggests that EURO returns exhibit a mid-week strengthening pattern.

A sub-period review reveals that this effect is far from stable. In the 2001-2006 period, none of the weekday coefficients are statistically significant, implying an absence of systematic weekday behaviour during the early years. In contrast, during the 2009–2014 post-crisis period, the anomaly becomes highly pronounced: Tuesday (0.002038, p = 0.0001), Wednesday (0.001574, p = 0.0036), and Thursday (0.001326, p = 0.0139) all exhibit strong positive returns. This period marks the strongest weekday anomaly in the entire sample, indicating persistent mid-week price appreciation.

However, during 2015-2019 and 2021-2024, the weekday pattern dissipates once again, with no coefficients attaining statistical significance at conventional levels. These results point to non-linear, time-varying weekday effects, where mid-week returns strengthen during market stress or regime shifts but weaken during more stable periods.

The full-sample Month-of-the-Year regression highlights a notable seasonal pattern. Several months show statistically significant positive returns: April (0.000924, p = 0.0197), May (0.000762, p = 0.0447), June (0.000829, p = 0.0280), August (0.001081, p = 0.0046), November (0.000784, p = 0.0421), and December (0.000867, p = 0.0218). This clustering of significant months suggests that EURO returns exhibit seasonal strength particularly in Q2 (April-June) and late-year months (August, November, December).

The anomaly, however, varies substantially across sub-periods. In 2001-2006, April (p = 0.0341) and May (p = 0.0462) emerge as the only significant months, indicating early-sample strength during spring. For 2009-2014, June (p = 0.0214) and August (p = 0.0062) produce strong monthly effects, again consistent with mid-year strength. The patterns weaken substantially during 2015-2019 and 2021-2024, where none of the months display significant abnormal returns. Thus, while seasonality exists in the overall sample, its periodicity shifts across time, weakening in the most recent decade.

The Half-Year regressions yield no statistically significant coefficients in the full sample or in any sub-period. The Second Half Year dummy never attains significance (all p-values > 0.25), suggesting that EURO returns do not follow a meaningful biannual return pattern.

Similarly, the Half-Month (Second-Half-of-the-Month) regressions show no evidence of anomalous returns across the full sample or any sub-period. Coefficients remain small and insignificant, indicating an absence of within-month return asymmetry in EURO markets.

Unlike the Half-Month pattern, the Turn-of-the-Month (TOM) regression reveals meaningful anomalies. In the full sample, TOM exhibits a statistically significant negative coefficient of –0.000400 (p = 0.0427), indicating that EURO returns tend to decline during TOM windows rather than strengthen, contrary to typical TOM findings in equity markets.

When broken into sub-periods, the effect becomes sharper. In 2009-2014, TOM is significantly negative at –0.001099 (p = 0.0104), reflecting consistent return drops around month-ends in this period. All other periods, however, show no significant TOM patterns. Overall, the TOM effect in EURO markets appears episodic and contrary in direction to classical TOM anomalies documented in stock markets.

Across the full sample and all sub-periods, the Turn-of-the-Year dummy (TOY) remains statistically insignificant. The EURO market does not exhibit the typical January or year-turn return premium seen in many equity markets. For instance, the full-sample coefficient (–0.000299, p = 0.3604) and all sub-period estimations fail to indicate any year-end or new-year return anomaly.

The full-sample Week-of-the-Month regression reveals some statistically significant early-month effects. Second Week (0.000573, p = 0.0252) and Third Week (0.000662, p = 0.0103) show positive return anomalies, with the third week displaying the strongest effect. This suggests that EURO returns tend to strengthen during the centre weeks of the month.

The anomaly becomes especially pronounced in the 2009-2014 period, where all mid-month weeks show strong significant coefficients: Second Week (p = 0.0132), Third Week (p = 0.0009), and Fourth Week (p = 0.0059). This period again mirrors the pattern seen in the weekday and month-of-year regressions, reinforcing that the post-crisis regime (2009–2014) shows the strongest and broadest set of calendar anomalies.

In contrast, 2001-2006, 2015-2019, and 2021-2024 yield insignificant coefficients across all weeks, showing no weekly within-month effects.

Table 5.3: Significant calendar anomalies in GBP/INR returns

		GBP/INR						
Period		**DOW**	**MOY**	**HY**	**HM**	**TOM**	**TOY**	**WOM**
Full (2001-2024)	Result	Tue, Wed, Thur	NS	NS	NS	Yes	NS	3, 5
	Sign	Highest				Lowest		Highest
2001-2006	Result	NS	May	NS	NS	NS	NS	NS
	Sign		Highest					
2009-2014	Result	Tue, Wed, Thur	April, June, August	NS	NS	NS	NS	3
	Sign	Highest	Highest					Highest
2015-2019	Result	Thur	NS	NS	NS	Yes	NS	3
	Sign	Highest				Lowest		Highest
2021-2024	Result	NS	NS	NS	NS	NS	NS	2
	Sign							Highest

Note: 'NS' indicates statistically insignificant.

The stationarity assessment using the Augmented Dickey–Fuller (ADF) test confirms that the Pound Sterling return series is highly stationary, with an ADF statistic of –74.54 ($p = 0.0001$). This strong rejection of the unit-root hypothesis ensures that all subsequent regressions on daily, monthly, half-month, half-year, turn-of-the-month, turn-of-the-year, and week-of-month dummy variables are statistically valid and free from issues of non-stationarity.

Across the full sample from 2001 to 2024, the Day-of-the-Week regressions reveal a mild but statistically meaningful weekday seasonality pattern. Tuesday exhibits a positive and significant coefficient (0.000852; $p = 0.0008$), suggesting that the Pound Sterling tends to generate higher returns on Tuesdays relative to Monday. Wednesday and Thursday also show significantly positive effects (0.000598; $p = 0.0191$ and 0.000586; $p = 0.0216$ respectively), representing a mid-week return strengthening. Friday returns, in contrast, remain statistically insignificant. The joint significance of the weekday dummies ($F = 3.77$, $p = 0.0045$) confirms that weekday effects are present for the full sample.

However, subsample analyses reveal that this weekday anomaly is not stable over time. During 2001-2006, none of the weekday coefficients are significant, indicating no detectable anomaly. The mid-week pattern re-emerges strongly in 2009–2014, where Tuesday (0.001851; p = 0.0009) and Wednesday (0.001165; p = 0.0384) generate unusually strong returns, with Thursday almost borderline significant (p = 0.0523). Yet, in 2015-2019 and again in 2021-2024, the weekday effects vanish entirely, with all weekday coefficients becoming statistically insignificant and the joint F-tests confirming model insignificance. This cyclical appearance and disappearance of weekday anomalies suggests that any exploitable pattern in Pound Sterling returns is episodic rather than persistent possibly a reflection of shifting global liquidity cycles, changing macroeconomic regimes, or structural adjustments in the FX markets.

Turning to the Month-of-the-Year regressions, the evidence for monthly seasonality is notably weak. For the full sample (2001–2024), none of the months produce statistically significant coefficients, and the F-statistic (1.03; p = 0.408) confirms the absence of joint monthly effects. Subperiod regressions reinforce this conclusion: during 2001-2006, 2009-2014, 2015-2019, and 2021-2024, monthly dummies remain uniformly insignificant. While a few months exhibit marginal t-values (such as April in 2009-2014 with p = 0.0842, and May in 2001-2006 with p = 0.0891), none meet conventional significance thresholds. The overall inference is clear: the Pound Sterling does not demonstrate stable or exploitable month-of-the-year patterns, unlike some equity markets where January or December effects are commonly observed.

Similarly, the Half-Year and Half-Month regressions offer no statistical evidence of calendar-based segmentation effects. All coefficients across all periods are insignificant, and the F-statistics remain far from significance (e.g., full sample Half-Year F = 0.03, p = 0.851; Half-Month F = 0.84, p = 0.359). These results indicate that dividing the year or month into halves does not meaningfully explain variations in the returns of the Pound Sterling.

The Turn-of-the-Month (TOM) effect displays mixed but noteworthy behaviour. In the full sample, TOM has a negative coefficient (–0.000381) that is marginally insignificant (p = 0.0603), suggesting a tendency for returns to be slightly lower during the TOM window. The effect is insignificant in 2001-2006 and 2009-2014, but becomes statistically significant during 2015-2019 (–0.000882; p = 0.047). This indicates a temporary, period-specific TOM anomaly where Pound Sterling returns tended to dip during the last and first trading days of the month, contrary to the positive TOM effect documented in many equity markets. The absence of significance in 2021–2024 suggests that the anomaly dissipated in the post-pandemic phase.

In contrast, the Turn-of-the-Year (TOY) analysis reveals no significant seasonal behaviour across any sample period. The full-sample TOY coefficient (–0.000435; p = 0.195) and all subsequent subsample coefficients remain far from statistical significance, indicating that year-end or year-beginning trading does not systematically influence Pound Sterling returns.

The Week-of-the-Month regressions provide one of the few compelling signs of seasonal anomalies in the currency. For the full sample, the third week shows a strong and significant positive coefficient (0.000807; p = 0.0023), suggesting that Pound Sterling returns tend to be higher during the third week of each month. The fifth week is borderline significant (0.000567; p = 0.0521), indicating a mild return uptick in months containing a fifth week. Joint significance (F = 2.60; p = 0.0339) confirms that week-of-month patterns matter in the overall period. Subsample analyses reveal partial replication: for 2009-2014, the third week again becomes significant (0.001166; p ≈ 0.045), reinforcing the full-sample pattern. However, the anomaly disappears in 2001-2006, 2015-2019, and 2021-2024 again illustrating that calendar effects in FX markets are episodic rather than persistent.

Table 5.4: Significant calendar anomalies in JPY/INR returns

JPY/INR								
Period		**DOW**	**MOY**	**HY**	**HM**	**TOM**	**TOY**	**WOM**
Full (2001-2024)	Result	Tue	August	NS	NS	Yes	NS	2,3,4,5
	Sign	Highest	Highest			Lowest		Highest
2001-2006	Result	NS	May	NS	NS	NS	NS	2,3,4,5
	Sign		Highest					Highest
2009-2014	Result	Tue	August	NS	NS	Yes	NS	3,4,5
	Sign	Highest	Highest			Lowest		Highest
2015-2019	Result	Wed, Fri	March, Oct, Nov	NS	NS	NS	NS	NS
	Sign	Lowest	Lowest					
2021-2024	Result	NS	July, Nov	Yes	NS	Yes	NS	NS
	Sign		Highest	Highest		Highest		

Note: 'NS' indicates statistically insignificant.

The Augmented Dickey–Fuller (ADF) test strongly rejects the null hypothesis of a unit root for the Japanese Yen return series (ADF statistic = –78.20; p = 0.0001), confirming that the returns are stationary and suitable for regression-based anomaly testing. The examination of day-of-the-week effects across the full sample (2001–2024) indicates no statistically meaningful weekday pattern, as none of the daily dummy variables achieve significance at conventional levels. The overall F-statistic (p = 0.067) suggests only a marginal joint effect. However, when the analysis is segmented, a clear anomaly emerges during 2009–2014, where Tuesday exhibits a significantly positive coefficient of 0.002227 (p = 0.0031), implying abnormally higher Yen returns on Tuesdays relative to Mondays in the post-crisis period. No other weekday shows significance in this or any other sub-period. Interestingly, in 2015–2019, Friday displays a significant negative return (–0.001436; p = 0.0142), hinting at a weak reversal tendency toward the end of the week. These results suggest that day-of-the-week anomalies in the Yen market are episodic emerging in certain macro-financial environments but not persistent across time.

The Month-of-the-Year analysis provides similarly limited evidence. In the full sample, August is the only month demonstrating a statistically significant positive return (0.000977; p = 0.0416), suggesting seasonally stronger Yen performance during the late summer. Sub-period analysis reveals occasional short-lived monthly effects, such as a positive and statistically significant May effect in 2001-2006 (0.001564; p = 0.0388). In the most recent period (2021-2024), both July (0.00199; p = 0.0402) and November (0.002015; p = 0.0420) register significant coefficients, indicating stronger returns in mid-summer and late autumn. However, these month-specific anomalies are neither large nor consistent enough across subsamples to indicate a persistent structural pattern.

With respect to turn-based anomalies, the Turn-of-the-Month (TOM) effect reveals intermittent significance. In the full sample, TOM returns are marginally negative (–0.000475) and close to significance (p = 0.0559). The only period showing a robust TOM effect is 2009-2014, where the coefficient becomes strongly negative (–0.001802; p = 0.0026), indicating lower Yen returns precisely at month-end or month-start a reverse of the typical equity market TOM pattern. No other period demonstrates a meaningful TOM relationship. The Turn-of-the-Year (TOY) effect shows no evidence of seasonal year-end or year-beginning return patterns, with all coefficients insignificant across the full sample and subsamples.

Half-Month and Half-Year anomalies likewise appear largely absent. Neither the Second-Half-Month dummy nor the Second-Half-Year dummy produces significance for the overall or most sub-periods. The only exception is the 2021–2024 period, where the Second Half of the Year shows a clearly positive and significant effect (0.00106; $p = 0.0082$), suggesting stronger Yen performance in the July-December interval in the post-pandemic monetary environment. This may reflect cyclical central-bank-driven currency dynamics rather than behavioural calendar effects.

In contrast, the Week-of-the-Month analysis reveals the strongest and most persistent anomaly in the Yen market. For the full sample, all weekly dummies from the second to fifth week show significant positive coefficients Second Week (0.000896; $p = 0.0054$), Third Week (0.000854; $p = 0.0085$), Fourth Week (0.000725; $p = 0.0251$), and Fifth Week (0.000796; $p = 0.0262$) indicating systematically higher returns compared to the first week. The anomaly is not only statistically robust but also economically meaningful. Sub-period analysis confirms that this effect is strongest during 2001-2006, where the second, third and fifth weeks exhibit coefficient values exceeding 0.0012 with high statistical significance ($p < 0.02$), and again in 2009-2014 where the pattern is partially sustained. This suggests that the Yen market may experience liquidity or informational cycles aligned with monthly trading flows, making the Week-of-the-Month effect the most durable anomaly in this asset.

Chapter 6

Findings and Conclusion

This section provides the findings and conclusions drawn for each objective of the study, policy implications, contribution of the study, and scope for future research.

6.1 Findings of the Study

6.1.1 Findings from Objective I Analysis

Automobile (Nifty Auto)

For the Auto sector, calendar anomalies are pervasive across CC, CO and OC windows. On a CC basis, Tuesday and Friday register significant effects, while CO returns also show a Tuesday anomaly and OC returns concentrate gains on Friday indicating that overnight information pushes prices into Tuesday opens, whereas intra-day trading on Fridays generates strongest trading-hour gains. April is the dominant month in OC returns. The TOM effect is robust in both CC and CO, confirming that both overnight adjustments and full-day dynamics contribute to month-end/start gains. The half-yearly effect appears in CO, suggesting structural overnight rebalancing mid-year. The WOM patterns are notable that is week 4 is lowest on CC, and CO shows weeks 2 to 4 as weak, implying mid-to-late-month overnight downward pressure even though Friday OC buying partially offsets losses intra-day.

Bank (Nifty Bank)

Banking sector anomalies are strongest during trading hours. OC returns show significant Friday effects and both CC and OC identify April and September as high-return months. TOM is uniformly significant across CC, CO, and OC, indicating that month-turn anomalies in banks arise from a mix of overnight positioning and intra-day flows. WOM shows weakness in CO for week 2, implying some overnight mid-month corrections. Overall, banking seasonality appears trader-driven but reinforced by overnight adjustments.

Consumer Durables (Nifty Consumer Durables)

Consumer Durables display mixed overnight and intraday patterns. CC returns show a Tuesday DOW effect and MOY effects for July and September; CO returns capture negative/contrasting signals in March and October, while OC returns highlight August as the strongest month. TOM is significant in CC and OC, suggesting both full-day and intraday month-turn gains. HM is significant in CO (lowest), indicating an overnight mid-month dip. WOM indicates that week 3 and 4 are lowest (CC), while week 5 records the highest OC returns a pattern consistent with intra-month profit-taking followed by end-month trading strength.

Financial Services (Nifty Financial Services)

Financial Services show distinct DOW effects (Tuesday and Friday) in CC and OC, with OC Friday particularly strong. MOY effects center on October (CC) and November (OC), indicating seasonal intraday opportunities. TOM is prominent in CO (overnight), suggesting that end-of-month positioning rather than daytime trades drive the month-turn gains. WOM and other sub-period effects are generally muted.

FMCG (Nifty FMCG)

FMCG anomalies are concentrated in mid-week trading. CC returns show Tuesday and Wednesday effects, with OC returns (Wednesday) delivering the highest intraday gains. July is the standout month in CC, while OC captures March, June and July as strong months. TOM is present in CO, indicating overnight repositioning at month boundaries. WOM signals are mixed: CC suggests week 5 positive, while CO shows weeks 2 and 5 negative pointing to complex overnight/intraday sentiment shifts around the month's end.

Health Care (Nifty Health Care)

Health Care presents relatively fewer anomalies, but notable month and mid-period effects. July is significant in both CC and OC, implying intraday strengthening in that month. HY and TOM appear in CO, indicating overnight mid-year and month-turn adjustments rather than intraday trading activity. WOM shows week 3 as lowest (CO) and week 5 as highest (OC), again pointing to overnight weakness followed by intraday recoveries late in the month.

Information Technology (Nifty IT)

IT anomalies are characterized by overnight weaknesses and specific intraday month effects. CO returns show a Friday DOW effect (negative), while CC identifies May as a low month and OC shows July as consistently the highest month and the strongest intraday period. HY and TOM are significant in CC (full-day), suggesting the IT sector's half-year and month-turn gains are captured over full trading sessions, though WOM effects are concentrated in OC (weeks 2 to 4) indicating structured intraday positioning across the month.

Media (Nifty Media)

Media exhibits strong, multi-window anomalies. CC shows Tuesday-Thursday DOW effects; OC (Wednesday, Thursday) captures the strongest intraday gains. MOY effects differ by window: CO flags March as lowest while OC highlights July as highest, suggesting overnight negative shocks in March but intraday rallies in July. HY and TOM are significant across CC and OC, showing robustness of mid-year and month-turn seasonality. WOM shows weeks 2 to 4 weaker across CC/OC, consistent with mid-month pressure.

Metal (Nifty Metal)

Metals display a strong April monthly effect in CC and OC, with TOM also significant in these windows pointing to intraday month-turn activity that produces higher April returns. WOM is consistently weak in mid-weeks (weeks 2 to 4) across CO and OC. Other DOW and HM effects are generally absent.

Oil & Gas (Nifty Oil & Gas)

Oil & Gas anomalies are largely overnight-driven. CO identifies February and HM (half-month) as lowest, and TOM appears in CO, indicating that month-turn and mid-month positioning in this sector are influenced by overnight global commodity news and price adjustments rather than domestic intraday trading. WOM shows weeks 3 to 5 weak in CO.

Pharma (Nifty Pharma)

Pharma shows persistent multi-window anomalies and is among the most anomaly-rich sectors. DOW effects (Tue, Wed, Fri) appear across CC and OC; CO also shows Wednesday effects. MOY effects for April and July are robust across CC/CO/OC, while June shows intraday strength (OC). TOM is significant in all windows, and HY appears in

CO indicating both overnight and intraday drivers. WOM indicates week 5 is positive (OC/CC) and week 2 negative (CO), underpinning alternating overnight weakness and intraday strength.

Private Banks (Nifty Private Bank)

Private Banks display Tuesday DOW effects in CC and CO, and Friday OC returns record the highest intraday gains. MOY, HY and TOM effects are largely absent, suggesting DOW seasonality dominates and that anomalies are concentrated in specific weekdays with intraday amplification on Fridays.

PSU Banks (Nifty PSU)

PSU Banks primarily show a robust TOM effect in CC and CO, suggesting month-turn repositioning reflected in overnight and full-day returns. WOM suggests weakness in week 4 (CC/OC) and CO shows weeks 2-3 weakness, indicating mid-month overnight corrections for public sector banks.

Realty (Nifty Realty)

Realty's seasonality is characterized by mid-month and month-turn patterns. HM (half-month) anomalies are significant in CC and OC and appear negative (lowest), while TOM is significant in CC and OC with highest returns at month turn. MOY shows August weakness in CO. WOM (weeks 2-4) is consistently weak in CC and OC, implying sustained mid-month underperformance partly offset by month-turn activity.

Market Index (Nifty50)

The Nifty50 confirms broad-market seasonality: Wednesday DOW effects are strongest across CC and OC (with CO also showing Tuesday and Wednesday), and MOY effects identify December (CC) and April/November/December (OC) as strongest months, while August is the weakest on CO. TOM and TOY are robust in CC and OC, TOM appears across CC/CO/OC indicating that month-turn and year-turn adjustments are systemic. WOM shows weeks 2 to 4 as generally weak across measures, signalling mid-month pressure at market level.

6.1.2 Findings from Objective II Analysis

Large-Cap Index (Nifty 100)

Positive returns on Tuesdays and Fridays may reflect institutional trading patterns and investor sentiment. Mondays can show negative returns due to weekend news adjustments, while Fridays often see higher returns as traders square off positions before the weekend. Large-cap stocks are generally more liquid and widely held, so market-wide behavioral patterns like optimism midweek can lead to consistent positive returns. The positive TOM effect indicates that large-cap stocks benefit from systematic inflows of funds at month-end/start, possibly due to salary-based investments, mutual fund allocations, and institutional portfolio rebalancing. The company’s usually wait for the month end to make announcement that might be positive or negative news but investor are always hopeful to get good news so they react in advance before the news is announced and this momentum continues for the month in which news is announced. Also, due to the fact that most of the investors are salaried person and usually get the salary at the end of the month. Negative returns in week 4 may be due to pre-month-end profit-taking or portfolio adjustments by large institutional investors, suggesting that the last week of the month is often a consolidation or cautious period. Insignificant, possibly because large-cap stocks are already well-analyzed, and seasonal effects may be less pronounced due to their stability and broader diversification.

Mid-Cap Index (MIDCAP 150)

Positive returns on Wednesdays suggest mid-week trading momentum in mid-cap stocks. These firms are less liquid than large-caps, so smaller institutional trades or investor optimism midweek can create noticeable patterns. Positive returns in April align with the start of India’s financial year, when new budgets, inflows, and investor optimism often favour mid-sized firms. This effect highlights sensitivity of mid-caps to macroeconomic and policy cycles. Positive returns suggest that mid-cap stocks, like large-caps, benefit from systematic month-start investments and investor optimism. Negative in weeks 2 to 4 could indicate mid-month profit booking or higher volatility typical of mid-cap stocks, which react more sharply to market news and liquidity fluctuations. Insignificant, possibly due to mid-caps being sensitive to specific market events rather than broad seasonal cycles.

Small-Cap Index (SMALLCAP 250)

Positive in April and October, reflecting strong seasonal performance at the financial year start and festive or monsoon-related periods, when investors often speculate in smaller, high-growth firms. Small-cap stocks are more prone to seasonal optimism and market sentiment swings. Positive, suggesting that even small-cap stocks receive inflows during month-end/start cycles, possibly amplified by retail investor participation. Positive returns at the turn of the year indicate that small-cap stocks may attract speculative interest or portfolio rebalancing activity at year-end. Mixed pattern (negative in week 3, positive in week 5) highlights higher volatility and susceptibility to short-term events, which is typical for smaller firms with lower liquidity and higher risk. Insignificant, reflecting that daily or semi-annual effects are less predictable in small-caps, dominated by firm-specific factors rather than systematic patterns.

Large-cap stocks are highly liquid, so anomalies are more muted except for systemic inflows (TOM, DOW). Mid- and small-cap stocks, being less liquid, display more pronounced anomalies due to limited trading and higher sensitivity to investor behaviour. Large-caps are dominated by institutional investors, while mid- and small-caps have a higher proportion of retail investors who follow seasonal or calendar-driven strategies. Calendar anomalies may reflect investor optimism, end-of-period portfolio rebalancing, or psychological biases that manifest differently across firm sizes.

6.1.3 Findings from Objective III Analysis

Brazil (Bovespa Index (IBOV))

In the case of Brazil, the analysis reveals notable seasonal anomalies across multiple dimensions. A positive DOW effect is observed on Wednesdays, suggesting mid-week trading tends to yield favourable returns. In contrast, the MOY effect highlights May and June as periods of significant underperformance, which partially supports the adage "Sell in May and go away." The half-year effect also appears, with the latter half of the year generating positive returns, possibly due to stronger macroeconomic performance and institutional portfolio rebalancing in this period. Liquidity-driven anomalies are particularly pronounced in Brazil, as both the TOM and TOY effects are positive, indicating consistent gains during transition periods. However, the Week-of-the-Month effect demonstrates that weeks two through five are largely negative, suggesting that most gains are concentrated early in the month. Overall, Brazil presents a mix of structural weaknesses in certain calendar windows, but the dominance of liquidity-driven anomalies indicates that timing strategies around the turn of periods may prove effective.

China (Shanghai Composite Index)

China's stock market exhibits a distinctly negative seasonal pattern, particularly concentrated around certain time windows. A negative DOW effect is detected on Thursdays, indicating a systematic mid-week underperformance. Month-of-the-Year effects reveal that June, August, and September are characterized by negative returns, which may reflect seasonal macroeconomic slowdowns and heightened market uncertainty during these periods. The Half-Month effect is also evident, with the second half of the month showing consistent underperformance, potentially linked to settlement cycles and liquidity constraints. Despite these weaknesses, the Turn-of-the-Month effect remains positive, suggesting that liquidity injection and institutional flows at the month's start sustain a strong anomaly, in line with international evidence. On the other hand, both the Week-of-the-Month and general market patterns point to persistent negative returns across multiple windows. Thus, while China exhibits a strong liquidity-based TOM anomaly, its broader calendar effects reflect structural tendencies toward underperformance during mid-month and late-year periods.

India (Nifty50)

The Indian equity market reflects limited but distinctive seasonal anomalies. The DOW effect appears absent, suggesting that daily return patterns are not systematically biased across the trading week. However, a positive MOY effect is observed in May, which diverges from the conventional global evidence of May weakness. This anomaly may be linked to unique institutional flows, fiscal calendar considerations, or local investor behaviour. More importantly, the TOM effect is strongly positive, reaffirming the global evidence of liquidity-driven gains around month transitions. Other anomalies, such as Half-Year, Half-Month, and TOY, are not significant in the Indian case, indicating that the market is relatively efficient outside these specific windows. Overall, India demonstrates a restrained anomaly structure, with the May effect and the robust TOM anomaly standing out as the most significant seasonal irregularities.

Indonesia (Jakarta Stock Exchange)

Indonesia presents one of the strongest anomaly patterns among the sampled emerging markets. Remarkably, all days of the trading week generate positive returns, suggesting a broadly favourable environment across the weekly cycle. This generalized positivity departs from the heterogeneous DOW patterns observed in other countries and may be attributed to structural market momentum or consistent capital inflows. The TOM and TOY effects are both positive, underlining the significance of liquidity-driven rallies during period transitions. Nonetheless, the Week-of-the-Month effect indicates that the second, fourth, and fifth weeks are negative, which suggests that gains are heavily concentrated at the start and mid-points of the month. Taken together, Indonesia exhibits a strong baseline of positive daily returns reinforced by liquidity anomalies, though mid-month weaknesses still persist.

Mexico (BMV IPC)

The Mexican stock market displays a mixed set of anomalies, with evidence of both structural weaknesses and liquidity-driven strengths. At the monthly level, February is associated with negative returns, which may reflect seasonal corporate reporting cycles or investor portfolio adjustments early in the year. On the other hand, both the TOM and TOY effects are positive, indicating strong liquidity-driven gains during these transition periods. Similar to Brazil and Russia, the Week-of-the-Month effect is negative for weeks two through five, concentrating the majority of gains in the early part of the month. The DOW anomalies appear insignificant, suggesting no consistent daily return bias. Overall, Mexico's anomaly structure highlights a dual nature: weakness in mid-month and mid-year windows, countered by strong gains around the month-end and year-end.

Russia (IMOEX)

Russia demonstrates one of the most striking seasonal anomaly patterns, as its market exhibits pervasive weaknesses across multiple horizons. The Day-of-the-Week effect is uniformly negative across all days, indicating systematic underperformance. Similarly, the MOY analysis reveals negative returns in March and May, aligning with the seasonal downturns observed in other emerging markets such as Brazil and Turkey. Despite this broad structural weakness, liquidity-driven anomalies persist, both the TOM and TOY effects are positive, which suggests that institutional flows at critical transition periods generate temporary boosts in returns. The Week-of-the-Month effect is consistently negative for weeks two through five, reinforcing the theme that gains, if any, are concentrated only in the very early part of the month. Thus, Russia presents a paradoxical case where widespread seasonal weaknesses dominate, yet liquidity anomalies remain resilient.

Turkey (BIST 100)

Turkey's equity market reflects broad seasonal weaknesses with only limited evidence of positive anomalies. The DOW effect is negative on Tuesdays, while the Month-of-the-Year effect highlights February, March, May, June, and August as months of underperformance. This widespread monthly weakness suggests structural seasonality tied to both domestic and international economic cycles. The only significant positive anomaly arises from the TOM effect, reaffirming the importance of liquidity-driven cycles, even in structurally weaker markets. Other anomalies, including the TOY and Week-of-the-Month effects, appear absent, further emphasizing the market's bias toward negative seasonal performance. Overall, Turkey demonstrates limited anomaly strength, with only the TOM effect persisting against a background of broad seasonal weakness.

Variance equation output in all indices suggested that negative shocks (bad news) increase volatility more strongly than positive shocks of equal magnitude, a common feature in equity markets. The lagged conditional variance term, GARCH(-1) demonstrated strong volatility persistence. This implies that volatility shocks are long-lasting and that periods of high volatility are likely to be followed by further high volatility.

6.1.4 Findings from Objective IV Analysis

When analysing INR returns in USD terms over the full period from 2001 to 2024, several calendar anomalies emerged with varying intensity across sub-periods. The DOW effect consistently highlighted Tuesday as a positive return day during 2001-2006 and 2009-2014, while this trend reversed partially in the 2015-2019 phase, where Friday showed negative returns, and no significant effect was observed in the most recent period (2021-2024). The Month-of-the-Year effect revealed strong seasonal tendencies, with May, August, and November showing positive returns across the full sample. However, sub-period analysis uncovered heterogeneity: during 2001-2006, April and May were favourable, while in 2009-2014, the same three months (August and November) continued to generate positive returns. By contrast, during 2015-2019, March produced negative returns whereas August showed positive performance, and no MOY effect appeared in 2021-2024. The TOM effect was highly persistent, being consistently negative across all sub-periods (2001-2019), reflecting systematic losses around month transitions, while this anomaly faded in the latest period (2021-2024). No evidence was found for the Half-Month or Turn-of-the-Year effects in any sub-period, indicating their irrelevance for this market. Lastly, the Week-of-the-Month effect displayed meaningful results, with positive returns during the 2nd and 3rd weeks (2001-2006), concentrated mainly in the 3rd week (2009-2014), but disappearing in later years. These findings suggest that while INR returns in USD terms once exhibited strong seasonal and weekly anomalies, particularly in the early years, their significance has diminished in the post-2020 phase, possibly reflecting increased market efficiency and structural shifts in currency dynamics.

For the Euro-denominated returns, the analysis over the full period (2001-2024) indicates a pronounced DOW effect, with Tuesday, Wednesday, and Thursday showing positive returns. This pattern remained consistent during 2009-2014, highlighting mid-week strength in euro-based trading, while in the most recent period (2021-2024), only Thursday retained a positive effect, suggesting partial persistence of this anomaly. The MOY effect was also significant, with April, May, June, July, August, November, and December demonstrating positive returns across the full sample. Sub-period results reinforce this seasonal strength, April and May were positive in 2001-2006, while April, June, and August stood out in 2009-2014. The effect, however, narrowed post-2015, with August alone showing positive performance, reflecting a gradual weakening of seasonality. The TOM effect was negative in both the full period and 2009-2014, indicating recurring losses around month-end transitions, though it disappeared in recent years. Additionally, the Week-of-the-Month effect revealed positive returns during the 2^{nd} and 3^{rd} weeks in the overall period and extended to the 4^{th} and 5^{th} weeks in 2009-2014, but this pattern later diminished.

Similarly, for Pound Sterling-denominated returns, a strong DOW effect emerged, with Tuesday, Wednesday, and Thursday yielding positive returns across the full period. This mid-week positivity persisted during 2009-2014 and 2015-2019, while Thursday remained the sole positive day in the 2021-2024 phase, suggesting a consolidation of weekly momentum effects toward the latter half of the week. The MOY effect was less pronounced but still notable, with May showing positive returns in 2001-2006 and April, June, and

August emerging as favourable months during 2009-2014. The TOM effect was consistently negative, particularly evident during the full sample and the 2021-2024 sub-period, reflecting potential investor rebalancing or liquidity adjustments near month-end. Finally, the Week-of-the-Month effect displayed positive returns in the 3rd and 5th weeks in the full period, with sustained positivity in the 3rd week across 2009-2019 and in the 2nd week during 2021-2024, indicating a recurring but gradually weakening intra-month rhythm in the pound market.

For the Japanese Yen (JPY) against the Indian rupee, the full-period analysis (2001-2024) reveals a positive DOW on Tuesdays, consistent with early-week strength also observed during 2009-2014. However, this pattern reversed in 2015-2019, when Wednesday and Friday recorded negative returns, indicating a shift in trading behaviour. The MOY effect showed August as a consistently positive month, while March, October, and November were negative during 2015–2019, and July and November turned positive in 2021-2024. The TOM effect, negative in earlier sub-periods, became positive in the most recent phase, suggesting changing market dynamics around month-end. A positive Half-Year effect also appeared after 2021, possibly linked to fiscal cycle adjustments. The Week-of-the-Month effect, evident in the early years (2nd to 5th weeks positive), weakened over time and disappeared after 2015. Overall, the yen's anomalies evolved from strong early-week and mid-month effects to a more recent positive TOM influence, reflecting shifting market timing behaviour and global liquidity conditions.

6.2 Conclusion

This study systematically investigated the presence of calendar anomalies across sectoral indices, size-based indices of the Indian stock market, select emerging equity markets, and foreign exchange returns. The findings offer a comprehensive understanding of the persistence, variation, and decline of calendar anomalies, thereby contributing to both academic discourse and practical investment strategy. With respect to Objective I, sectoral analysis of Indian equity markets revealed that anomalies are pervasive but heterogeneous across sectors. Trading and non-trading windows display distinct behaviours in certain sectors, such as Automobile, Pharma, and Media, exhibit multi-window anomalies that combine both overnight and intraday effects, while others, such as Health Care and Oil & Gas, show anomalies concentrated in overnight adjustments. The Turn of the Month effect is the most robust across nearly all sectors, underscoring its systemic nature. Day of the Week and Month of the Year effects, though present, are highly sector-specific, influenced by institutional flows, and intraday trader sentiment. Week-of-the-Month patterns generally point to mid-month weaknesses, further highlighting the structural timing of investor behaviour. In Objective II, the analysis of size-based indices demonstrates that liquidity and investor composition significantly shape anomaly patterns. Large-cap stocks, dominated by institutional investors, exhibit relatively muted anomalies except for the persistent TOM effect and some day-of-the-week regularities. Mid-cap and small-cap indices, however, show stronger and more volatile anomaly patterns, reflecting higher sensitivity to macroeconomic cycles, retail investor behaviour, and speculative trading. These findings indicate that market size and investor heterogeneity are key determinants of anomaly persistence, with smaller stocks amplifying behavioural and liquidity-driven irregularities.

For Objective III, the examination of emerging market indices highlights that anomalies are not unique to India but manifest differently across countries depending on structural, macroeconomic, and liquidity conditions. Brazil and Indonesia display strong liquidity-driven anomalies (TOM and TOY), while Russia and Turkey suffer from pervasive weaknesses across most windows, with liquidity effects being their only consistent source of positive returns. China and Mexico occupy middle ground, showing strong month-turn effects but also systematic mid-month underperformance. India, in comparison, reflects a more restrained anomaly structure, with only the May effect and a robust TOM anomaly being significant. These results illustrate that while liquidity cycles are nearly universal, country-specific economic structures and investor behaviour patterns dictate the direction and intensity of other seasonal effects. Finally, Objective IV provides evidence that foreign exchange returns (INR in USD, Euro, Pound Sterling and Japanese Yen) once displayed strong calendar anomalies, particularly during the 2009 and 2014, with Tuesday effects, positive month such as August, and a persistently negative TOM effect. However, in the most recent period (2021-2024), such anomalies have largely disappeared. This shift suggests that increasing global integration, improvements in market efficiency, and changes in capital flow dynamics have progressively eroded predictable seasonal patterns in currency markets.

Overall, the thesis reveals three unifying insights. First, the TOM effect emerges as the most consistent and cross-market anomaly, highlighting the role of institutional flows, portfolio rebalancing, and liquidity cycles. Second, anomaly intensity varies with market depth and structure that is large-cap and developed segments are relatively efficient, while mid- and small-cap indices, as well as structurally weaker emerging markets, display more pronounced seasonal irregularities. Third, anomalies are dynamic and evolving while earlier decades exhibited strong seasonal biases across equities and foreign exchange, recent evidence points to their weakening, particularly post-2020, as markets become more efficient and globally integrated. In conclusion, while calendar anomalies continue to exist in select markets and segments, their declining persistence underscores the adaptive efficiency of financial systems. For investors, this implies that anomaly-based strategies must be applied with caution, sectoral and size sensitivity, and an awareness of structural shifts over time. For scholars, the findings highlight the importance of dynamic, context-specific analyses rather than static anomaly generalizations, as calendar effects are not universal but evolve with market development, institutional behaviour, and global integration.

6.3 Policy Implication of Study

The persistence of calendar anomalies across Indian sectoral and size-based indices, as well as in emerging markets, suggests that regulators such as SEBI must remain vigilant in monitoring trading patterns to ensure that anomalies are not exploited through manipulative practices, particularly in mid- and small-cap segments where liquidity is low. The robustness of the Turn-of-the-Month effect highlights the influence of institutional flows, calling for policies that encourage staggered fund allocations to reduce concentrated month-end volatility. At the same time, investor education initiatives are essential to help retail investors avoid herd-driven trading based on perceived seasonal patterns. Cross-market evidence of liquidity-driven anomalies also underscores the need for international coordination on capital flow transparency, while the diminishing anomalies in foreign exchange market reflect the positive role of reforms that deepen derivatives and improve efficiency. Overall, policymakers should adopt a dynamic, evidence-driven approach, combining surveillance, education, and cross-border cooperation to strengthen market efficiency and protect diverse investor groups.

6.4 Contribution of the Study

This study makes several significant contributions to the literature on calendar anomalies and financial market efficiency. First, it provides one of the most comprehensive analyses of sectoral indices in the Indian equity market, examining both trading (OC) and non-trading (CO) returns alongside full-day (CC) measures. This multi-window approach uncovers nuanced differences between overnight adjustments and intraday trading dynamics, offering a richer perspective than studies limited to closing-to-closing returns. Second, by analyzing size-based indices (large-cap, mid-cap, and small-cap), the study highlights how market depth, liquidity, and investor composition shape the persistence of anomalies, with mid- and small-cap stocks displaying stronger seasonal effects due to retail dominance and lower liquidity. Third, by extending the investigation to select emerging markets, the research situates India within a broader comparative framework, showing both commonalities (such as the robustness of the TOM effect) and divergences (such as country-specific Month-of-the-Year patterns). Fourth, the inclusion of foreign exchange returns (USD, Euro, Pound Sterling, Japanese Yen) over a long horizon adds a cross-asset dimension, demonstrating how anomalies evolve and weaken over time as markets become more efficient and globally integrated. Finally, the study contributes practical insights for policymakers, regulators, and investors by demonstrating that while anomalies persist, they are dynamic, context-dependent, and increasingly sensitive to structural and institutional changes. In doing so, the research bridges sectoral, market-size, cross-country, and currency perspectives, offering a holistic understanding of calendar anomalies in both domestic and international contexts.

6.5 Scope for Further Research

Building on the findings of this study, several avenues for future research emerge. First, the use of intraday or high-frequency data could provide deeper insights into the microstructure of calendar anomalies, especially in understanding the interplay between overnight adjustments and intraday trading activity. Second, expanding the analysis to include a wider range of indices within India such as thematic, ESG-focused, or volatility-based indices would enrich the understanding of how anomalies manifest across different market segments. Finally, extending the cross-country comparison to a larger sample of emerging and developed markets could highlight global commonalities and structural differences in anomaly behaviour more comprehensively.

Research Paper Publication

1. Published paper titled “Empirical Evidence on Calendar Anomalies in Trading and Non-trading Day Returns in Indian Stock Market” in Finance India, September 2023, 0970-3772. (**SCOPUS)**

Research Paper Presented

1. Presented research paper titled "Empirical Evidence on Calendar Anomalies in Indian Spot Market" at the (IIF-IRCAS) Indian Institute of Finance, International Research Conference & Award Summit (Multi-Disciplinary Conference) on January 7th and 8th, 2023.

2. Secured Best Paper Award for the Research Paper presented titled "Empirical Evidence on Calendar Anomalies in Indian Spot Market". For the One Day National Level Conference (Hybrid) on “Digital Transformation Trends In Commerce: It’s Impact On Indian Economy” on 19th February 2022. Organized by Sant Sohirobanath Ambiye, Government College of Arts and Commerce, Virnoda, Pernem, Goa.

3. Presented Paper titled “Empirical Evidence on Existence of Calendar Anomaly in Nifty 50 using EGARCH Model” at 7th International Conference on contemporary issues in agriculture, engineering, management, information technology, life sciences, social sciences and humanities jointly organized by Nehru College of Management, India and Lincoln University College, Malaysia at Langkawi from 7th to 11th May 2019.

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ANNEXURE

Augmented Dickey-Fuller Test Statistic for Sectoral Indices Return Series

	t-Statistic		
Index	**CC**	**CO**	**OC**
Auto	-55.24389***	-21.9676***	-57.53699***
Bank	-63.20983***	-71.31463***	-67.86626***
Consumer Durables	-26.26337***	-26.87074***	-27.783***
Financial Services	-54.63484***	-22.12592***	-27.69806***
FMCG	-59.08655***	-22.84812***	-59.26102***
Health Care	-27.84537***	-28.18366***	-28.84885***
IT	-72.91705***	-72.4854***	-72.20602***
Media	-56.28458***	-19.20313***	-57.46951***
Metal	-57.51076***	-38.20653***	-59.82888***
Oil & Gas	-28.84895***	-17.34912***	-30.07636***
Pharma	-56.45986***	-21.19462***	-58.93837***
Private Bank	-45.14094***	-17.39806***	-22.26415***
PSU Bank	-56.55681***	-38.20965***	-59.48823***
Realty	-54.36039***	-19.87243***	-56.29655***
Nifty50	-80.34268***	-24.43156***	-61.07633***

Note: ‘***’ indicates significant at 1%.

Dummy Variable Regression Coefficients for Sectoral Indices Close to Close (CC) Return Series

Index	Auto	Bank	Consumer Durables	Financial Services	FMCG	Health Care	IT	Media	Metal	Oil & Gas	Pharma	Private Bank	PSU Bank	Realty	Nifty 50
Day-of-the-Week Effect															
C	-0.034898	-0.000822	-0.002286	-0.036541	-0.017006	-0.003126	0.036374	-0.113156*	-0.050304	0.077989	-0.048726	-0.08218	-0.023994	0.000312	-0.046129
TUE	0.181653**	0.073601	0.208245*	0.145769*	0.096836*	0.125503	0.050234	0.160449*	0.140109	0.024185	0.107719*	0.26636***	-0.002292	-0.014289	0.059464
WED	0.072914	0.0686	0.074907	0.090865	0.133646**	0.166833	0.062762	0.217724**	0.077703	-0.001649	0.151954**	0.156013	0.110158	0.110508	0.243068***
THUR	0.073872	0.028241	0.001749	0.09036	0.052026	-0.007464	-0.005804	0.192056**	0.109294	0.004179	0.044403	0.101955	-0.030831	0.050299	0.059734
FRI	0.127898*	0.101879	0.045709	0.131126*	0.083944	0.026666	-0.187497	0.054268	0.092381	-0.13522	0.164693***	0.131878	0.1046	-0.024064	0.087827
F-statistic	1.687507	0.494774	1.118679	1.076496	1.579909	1.19251	0.807907	2.057191*	0.571255	0.39787	2.51043**	1.93612	0.69469	0.547615	5.831054***
Durbin-Watson stat	1.92966	1.810307	1.808956	1.936954	2.014886	1.928259	2.007773	1.970654	2.013353	1.995808	1.922644	1.93493	1.927925	1.812308	1.892224
Month-of-the-Year Effect															
C	0.054695	-0.043761	-0.140008	-0.036647	-0.004954	-0.047268	-0.007255	-0.086309	-0.056879	0.109614	0.00122	0.01607	-0.010388	0.016071	-0.020159

FEB	-0.118557	-0.088949	0.173193	-0.034609	-0.035805	0.021924	0.000734	-0.083926	-0.011314	-0.253605	-0.076531	-0.028044	-0.167152	-0.105058	0.052427
MAR	-0.175628	0.025341	0.102561	0.029157	0.138572	0.150709	-0.012998	-0.049299	0.000463	0.063559	0.036939	-0.185997	0.024705	-0.059572	-0.00368
APRIL	0.192143	0.271931**	0.304933	0.180016	0.138873	0.111578	-0.022837	0.106299	0.297882*	0.106344	0.236605**	0.190874	0.101084	0.098141	0.126201
MAY	0.05862	0.138253	0.103171	0.130707	0.11235	-0.06407	-0.45444*	0.090864	0.03126	-0.227735	-0.110825	0.064244	-0.028115	0.050678	0.042059
JUNE	0.0239	0.0000215	0.212372	0.113341	0.08901	0.224895	0.072868	0.17017	0.078866	-0.053975	0.129351	0.018187	0.050152	0.041501	0.082716
JULY	0.003821	0.186025	0.405325**	0.114014	0.156643*	0.39468**	0.193134	0.218431	0.122482	0.186497	0.187231*	0.098772	0.028115	0.031916	0.096523
AUG	0.003738	0.022664	0.366776**	0.035398	0.047133	0.12403	0.134948	0.072471	0.07439	0.035397	0.067867	0.079344	-0.19037	-0.185941	0.050258
SEPT	0.035124	0.22496*	0.306487*	0.03998	0.019489	0.101873	0.091738	0.219644	0.04677	-0.131736	0.042507	-0.095012	-0.039913	0.080348	0.059592
OCT	0.053113	0.116816	0.012654	0.207263*	-0.016856	-0.063613	0.024594	0.135824	0.172966	-0.270808	0.014424	0.084261	0.281557	0.094336	-0.012794
NOV	-0.024712	0.163871	0.199444	0.197145	0.034866	0.172737	0.11587	0.131492	0.094073	0.019267	-0.041049	0.128442	0.206138	-0.00223	0.106633
DEC	-0.022992	0.107852	0.231466	0.081893	0.042268	0.121381	0.171993	0.148433	0.181125	-0.045682	0.039898	0.029493	0.020843	0.063553	0.167837**

F-statistic	1.183454	1.409388	1.081359	0.841246	1.095299	1.250985	0.967638	0.91704	0.690966	0.8395	2.17417**	0.874216	1.165457	0.549239	0.872741
Durbin-Watson stat	1.940096	1.81834	1.833935	1.943834	2.022382	1.955862	2.011858	1.975293	2.017866	2.015663	1.940231	1.946531	1.936085	1.814892	1.897559
Half-Year Effect															
C	0.050376	0.011479	0.006744	0.034471	0.069198***	0.025256	-0.078767	-0.046734	0.006117	0.044894	0.034625	0.026876	-0.014076	0.020192	0.028862
SECOND_HALF_YEAR	0.011777	0.081676	0.100987	0.040405	-0.025415	0.059815	0.194367*	0.114854**	0.053807	0.020974	0.02044	0.043526	0.051968	0.009052	0.029728
F-statistic	0.063126	2.557875	1.914245	0.681858	0.502463	0.83923	3.80648*	3.877871**	0.754217	0.052731	0.264313	0.496445	0.538577	0.017889	0.768313
Durbin-Watson stat	1.931872	1.813052	1.812903	1.939234	2.016331	1.927927	2.009131	1.972435	2.013889	1.996538	1.926203	1.938404	1.930252	1.812331	1.895098
Half-Month Effect															
C	0.09203***	0.069381*	0.099703*	0.068357*	0.044508*	0.060752	0.053956	0.048641	0.080837*	0.110447*	0.039513	0.07524*	0.044546	0.084431*	0.06585***
SECOND_HALF_MONTH	-0.069771	-0.030872	-0.070239	-0.026063	0.023197	-0.003388	-0.064769	-0.071605	-0.092378	-0.104925	0.010676	-0.050582	-0.063376	-0.116442*	-0.043127
F-statistic	2.217512	0.365406	0.940043	0.283652	0.418464	0.002733	0.422461	1.506356	2.224424	1.343316	0.07208	0.670789	0.800831	2.965627*	1.616557
Durbin-Watson stat	1.932608	1.812056	1.813276	1.938448	2.016313	1.926017	2.007788	1.970537	2.013596	1.999353	1.925915	1.937993	1.929831	1.813244	1.895128
Turn-of-the-Month Effect															
C	0.034476	0.021113	0.016415	0.044038	0.047393**	0.035263	-0.023731	-0.03958	-0.027939	0.026393	0.008466	0.037049	-0.025487	-0.05083	0.012447

TOM	0.112586*	0.167064***	0.241849***	0.056526	0.045947	0.123644	0.229323*	0.265218***	0.316288***	0.157919	0.187277***	0.062887	0.193405**	0.389397***	0.162154***
F-statistic	3.625844*	6.714053***	7.072423***	0.837697	1.030962	2.267834	3.320972*	13.0172***	16.4386***	1.891497	13.98326***	0.65217	4.687869**	20.89536***	14.30384***
Durbin-Watson stat	1.933779	1.813411	1.819968	1.939401	2.017023	1.929114	2.007222	1.978297	2.02495	2.002175	1.930645	1.938276	1.932477	1.823048	1.899089
Turn-of-the-Year Effect															
C	0.053816**	0.050825*	0.050876	0.058199**	0.055418***	0.045329	0.013759	0.009346	0.026798	0.042471	0.037456*	0.046753	0.017136	0.014601	0.035445**
TOY	0.040867	0.045185	0.196078	-0.051943	0.015406	0.208569	0.115824	0.043161	0.108426	0.217297	0.124463	0.042719	-0.081821	0.16539	0.13913*
F-statistic	0.180668	0.179189	1.799837	0.256757	0.041845	2.550489	0.31062	0.129998	0.727841	1.414191	2.22285	0.108547	0.302609	1.396135	3.819545*
Durbin-Watson stat	1.931973	1.811982	1.811793	1.938757	2.016015	1.931497	2.007661	1.970261	2.013899	1.999712	1.927222	1.938208	1.929958	1.813438	1.895626
Week-of-the-Month Effect															
C	0.114493*	0.116562*	0.181034**	0.122886**	0.062057	0.050726	0.108628	0.21798***	0.26726***	0.13426	0.080459	0.096775	0.17750**	0.25277***	0.16432***
SECOND WEEK	-0.028994	-0.100162	-0.114239	-0.086927	-0.041866	0.034397	-0.119636	-0.242935**	-0.27534***	0.036236	-0.075183	0.005083	-0.222706*	-0.22558**	-0.14712***
THIRD_WEEK	-0.087066	-0.07469	-0.241535**	-0.073494	0.011107	-0.146344	-0.065708	-0.295346***	-0.318954***	-0.243026	-0.094205	-0.118178	-0.179531	-0.319259***	-0.167254***

FOURTH_WEEK	-0.137858*	-0.105006	-0.235712**	-0.125513	-0.066065	0.026803	-0.256399	-0.288079***	-0.357874***	-0.198686	-0.061175	-0.125913	-0.249031**	-0.38913***	-0.167173***
FIFTH_WEEK	0.002312	0.011553	0.128462	-0.012437	0.112962*	0.180293	0.095989	-0.10412	-0.094941	0.102801	0.11873*	0.049797	-0.100426	-0.08657	-0.064094
F-statistic	1.337982	0.849955	3.479927***	0.85686	2.57845**	2.44648**	1.324342	3.54448***	4.50563***	2.27727*	3.197603**	1.309198	1.479438	4.20867***	3.45651***
Durbin-Watson stat	1.935402	1.812991	1.820767	1.93949	2.021563	1.944366	2.007962	1.979113	2.02517	2.011656	1.9342	1.940125	1.932223	1.821459	1.898065

Dummy Variable Regression Coefficients for Sectoral Indices Close to Open (CO) Return Series

Index	Auto	Bank	Consumer Durables	Financial Services	FMCG	Health Care	IT	Media	Metal	Oil & Gas	Pharma	Private Bank	PSU Bank	Realty	Nifty 50
Day-of-the-Week Effect															
C	0.119591***	0.114224***	0.139099***	0.081568***	0.09027***	0.094288***	0.064591	0.149004***	0.146997***	0.137138***	0.138478***	0.083784**	0.174349***	0.157587***	0.04693***
TUE	0.080486**	0.024067	0.064856	0.08092*	0.033331	0.05266	0.044208	0.024762	0.06247	0.069339	0.035621	0.136504**	0.046617	0.031854	0.031482*
WED	0.031373	-0.014295	0.042472	0.017683	0.029661	0.045936	0.057988	0.068324*	0.018806	0.037424	0.046037*	0.027454	0.01821	0.016205	0.076325***
THUR	0.003593	-0.015895	0.036421	0.019279	0.010091	0.037924	0.013558	0.029042	-0.002042	-0.005899	0.003415	-0.005028	0.00896	0.013561	0.015272

FRI	0.014081	-0.032003	0.035499	0.000351	0.030075	0.025608	-0.575335**	0.034926	0.0135	0.041572	0.002367	-0.02803	0.003867	-0.007629	0.022349
F-statistic	1.653802	0.560758	0.34437	1.290293	0.610888	0.472246	1.93762	0.759994	0.715168	0.508828	1.230649	2.630872**	0.320382	0.278746	4.989238***
Durbin-Watson stat	2.045436	2.053004	1.853774	2.050322	2.021501	1.950435	1.995603	1.805562	2.07045	1.783582	1.976027	2.100507	1.976266	1.885774	1.981891
Month-of-the-Year Effect															
C	0.14759***	0.119558***	0.076157	0.093629**	0.110485***	0.131935***	0.140551	0.215487***	0.180168***	0.151188**	0.137996***	0.114517*	0.213533***	0.203081***	0.103206***
FEB	-0.007359	-0.068253	-0.044894	-0.036366	-0.041586	-0.108765	-0.074838	-0.087725	-0.059731	-0.194499*	-0.019737	-0.084805	-0.043446	-0.10329	-0.017926
MARCH	-0.068424	-0.029413	0.190034**	-0.021274	-0.020835	0.013407	-0.126023	-0.172164***	-0.082371	0.025144	-0.005038	-0.125945	-0.06436	-0.094656	-0.043109
APRIL	0.005868	0.002558	0.108764	0.048921	0.009953	-0.003999	-0.041513	-0.017366	0.0321	0.070428	0.083366*	0.060641	-0.03381	0.009889	-0.027086
MAY	-0.017793	0.028855	0.087949	0.014455	0.030146	-0.069225	-0.572519	0.005378	0.008859	-0.000914	-0.010492	0.016927	0.021143	0.055658	-0.028872
JUNE	-0.047257	-0.064688	0.122458	-0.015891	-0.044299	-0.014078	-0.060366	-0.017182	-0.026627	0.145409	-0.023284	-0.001895	-0.064183	-0.034321	-0.037924
JULY	-0.009538	0.018346	0.14865	0.032647	0.026022	0.021081	-0.836753**	-0.037734	0.018273	0.091777	0.015433	0.066103	-0.036247	-0.021682	-0.020085

AUGUST	0.025303	-0.047843	0.086604	-0.002496	-0.018201	-0.024989	-0.058737	-0.081278	-0.0377	0.010394	0.028039	-0.011294	-0.057576	-0.106363*	-0.051129*
SEPT	0.012433	-0.028	0.113885	0.014739	0.021082	-0.012361	-0.023419	0.051176	-0.004126	-0.021984	0.063731	-0.045817	-0.022713	-0.049234	-0.038489
OCT	0.064316	0.024204	0.190059**	0.071948	0.035215	0.010451	-0.025236	-0.001668	-0.007482	0.022706	0.03981	0.045493	0.040469	-0.024438	-0.00057
NOV	0.014992	0.005456	0.087143	0.020926	-0.001453	0.040709	-0.051237	-0.058148	-0.028091	-0.004113	0.019003	0.032703	0.01404	-0.023178	-0.030163
DEC	0.000966	0.002229	0.076809	0.011286	0.007699	0.052733	-0.089266	-0.011478	0.008111	0.035913	0.031754	-0.020626	-0.033541	-0.02372	-0.030074
F-statistic	0.719083	0.601422	1.148928	0.427	0.846017	0.893307	0.773372	1.719002*	0.467516	1.271856	1.153024	0.840508	0.460711	1.13611	0.607809
Durbin-Watson stat	2.050636	2.056368	1.884423	2.054811	2.027647	1.970261	1.996517	1.817739	2.07414	1.806759	1.982228	2.109142	1.980912	1.8938	1.984772
Half-Year Effect															
C	0.124827***	0.097568***	0.152802***	0.091924***	0.099333***	0.100819***	-0.008465	0.168227***	0.158841***	0.15816***	0.140958***	0.093523***	0.182948***	0.175984***	0.077408***
SECOND_HALF_YEAR	0.040557*	0.017662	0.039226	0.026332	0.02289	0.045916*	-0.034116	0.023853	0.013215	0.012978	0.029823*	0.032119	0.013837	-0.014503	-0.002743
F-statistic	3.135874*	0.494093	1.201463	1.005	1.842863	2.855292*	0.038569	0.894468	0.228277	0.107258	2.913085*	0.805948	0.219392	0.312941	0.056331
Durbin-Watson stat	2.047581	2.053066	1.85805	2.052025	2.022813	1.955428	1.995921	1.806609	2.070859	1.786842	1.976813	2.100436	1.976551	1.8858	1.98249
Half-Month Effect															

C	0.154678***	0.10039***	0.2105***	0.109269***	0.113319***	0.143977***	-0.056146	0.180771***	0.175179***	0.207317***	0.156842***	0.113561***	0.187152***	0.165014***	0.077318***
SECOND_HALF_MONTH	-0.017789	0.012269	-0.069457*	-0.007702	-0.004724	-0.03368	0.059073	-0.000645	-0.018746	-0.081712**	-0.001572	-0.006772	0.005473	0.006735	-0.002532
F-statistic	0.602868	0.238521	3.840552*	0.085952	0.078425	1.558895	0.115654	0.000654	0.459418	4.343248**	0.00809	0.035829	0.03431	0.067554	0.047964
Durbin-Watson stat	2.045508	2.053095	1.860945	2.051204	2.021753	1.952401	1.995876	1.806022	2.070571	1.794193	1.975078	2.09957	1.976484	1.885712	1.982462
Turn-of-the-Month Effect															
C	0.132237***	0.093066***	0.168954***	0.094074***	0.103984***	0.114517***	0.030279	0.166368***	0.156292***	0.146207***	0.145***	0.097721***	0.177959***	0.166566***	0.069656***
TOM	0.068583**	0.070014**	0.0306	0.057805*	0.03553*	0.063595*	-0.289254	0.072251**	0.047828	0.100342**	0.056647**	0.063349	0.061507*	0.009731	0.032898**
F-statistic	5.633447**	4.871486**	0.467721	3.041852*	2.787702*	3.460544*	1.738431	5.158682**	1.878064	4.067263**	6.604042**	1.973934	2.722729*	0.088398	5.062954**
Durbin-Watson stat	2.048559	2.054839	1.857128	2.05215	2.023769	1.956998	1.997517	1.806504	2.072369	1.795256	1.977824	2.100069	1.97827	1.885711	1.98421
Turn-of-the-Year Effect															
C	0.143894***	0.10488***	0.178044***	0.104383***	0.109478***	0.120939***	-0.03463	0.180696***	0.162191***	0.166567***	0.153069***	0.109656***	0.189695***	0.165617***	0.074065***
TOY	0.02684	0.029411	-0.047246	0.015718	0.023712	0.088316	0.141846	-0.00401	0.053896	-0.016482	0.049266	0.007234	0.00415	0.045675	0.032496

F-statistic	0.326113	0.313768	0.43439	0.081577	0.448115	2.634277	0.153322	0.006005	0.902575	0.043149	1.80143	0.009278	0.004472	0.725393	1.793654
Durbin-Watson stat	2.045717	2.053032	1.855844	2.051353	2.02217	1.956512	1.99611	1.806032	2.071488	1.786432	1.976469	2.099645	1.976396	1.886205	1.98316
Week-of-the-Month Effect															
C	0.201172***	0.148106***	0.220186***	0.145602***	0.151957***	0.17683***	-0.338483	0.250672***	0.218563***	0.254406***	0.18361***	0.131103***	0.268622***	0.186356***	0.110845***
SECOND WEEK	-0.074802**	-0.068422*	0.013002	-0.06241	-0.073824***	-0.026355	0.409746	-0.130223***	-0.07904*	-0.025746	-0.052871*	-0.029985	-0.120412**	-0.046087	-0.049723***
THIRD_WEEK	-0.069593*	-0.062536	-0.095741	-0.037878	-0.040094	-0.098962**	0.440022	-0.066561	-0.055192	-0.168375***	-0.020754	-0.028285	-0.104752**	-0.012334	-0.041706**
FOURTH_WEEK	-0.074305**	-0.026639	-0.067166	-0.043922	-0.027795	-0.06668	0.239498	-0.063014	-0.063342	-0.111584*	-0.032924	-0.027034	-0.062584	-0.015757	-0.035887*
FIFTH_WEEK	-0.034562	-0.033962	-0.071588	-0.046724	-0.055582*	-0.038446	0.414151	-0.068536	-0.049489	-0.122243*	-0.019496	-0.008967	-0.082443	-0.004849	-0.036885*
F-statistic	1.472408	0.954988	1.518758	0.556734	2.083037*	1.577295	0.805534	2.593744**	0.831582	2.528887**	0.974118	0.102064	1.847141	0.401591	1.936724
Durbin-Watson stat	2.048961	2.055116	1.859219	2.053432	2.024502	1.960316	1.99431	1.810413	2.072849	1.803121	1.978044	2.100039	1.982	1.886624	1.984383

Dummy Variable Regression Coefficients for Sectoral Indices Open to Close (OC) Return Series

Index	Auto	Bank	Consumer	Financial	FMCG	Health Care	IT	Media	Metal	Oil & Gas	Pharma	Private Bank	PSU Bank	Realty	Nifty 50

			Durables	Services											
Day-of-the-Week Effect															
C	-0.154489***	-0.115045**	-0.141384*	-0.118108**	-0.107276***	-0.097414	-0.028217	-0.26216***	-0.197302***	-0.059148	-0.187203***	-0.165964***	-0.198342***	-0.157275**	-0.093058***
TUESDAY	0.101167	0.049533	0.143389	0.064849	0.063506	0.072843	0.006026	0.135686	0.077639	-0.045154	0.072098	0.129857	-0.048909	-0.046142	0.027983
WED	0.041541	0.082896	0.032434	0.073182	0.103985**	0.120897	0.004774	0.1494*	0.058898	-0.039073	0.105917*	0.128559	0.091949	0.094303	0.166743***
THUR	0.070279	0.044136	-0.034672	0.071081	0.041934	-0.045389	-0.019362	0.163013*	0.111337	0.010077	0.040988	0.106983	-0.039791	0.036738	0.044463
FRI	0.113817*	0.133883*	0.01021	0.130775**	0.053869	0.001058	0.387838	0.019343	0.078881	-0.176793	0.162326***	0.159907*	0.100734	-0.016435	0.065478
F-statistic	1.000837	0.986156	0.875942	1.002093	1.064036	0.947251	1.027078	1.667827	0.460212	0.69264	2.182645*	1.115644	0.964115	0.621857	3.210346**
Durbin-Watson stat	2.01264	1.951102	1.922345	2.04383	2.020293	1.997088	1.987579	2.012419	2.093252	2.075512	2.008306	2.014563	2.028245	1.881449	1.920472
Month-of-the-Year Effect															
C	-0.092894	-0.163319**	-0.216165*	-0.130276*	-0.115439**	-0.179203	-0.147806	-0.301797***	-0.237047**	-0.041574	-0.136776**	-0.098447	-0.223921**	-0.187011*	-0.123365**
FEB	-0.111198	-0.020696	0.218087	0.001757	0.005781	0.130689	0.075572	0.003799	0.048418	-0.059106	-0.056794	0.056761	-0.123706	-0.001768	0.070353

MARCH	-0.107204	0.054754	-0.087473	0.050431	0.159408**	0.137303	0.113025	0.122865	0.082834	0.038416	0.041977	-0.060052	0.089065	0.035084	0.039429
APRIL	0.186275*	0.269373**	0.196169	0.131095	0.12892	0.115577	0.018675	0.123665	0.265782*	0.035916	0.153239	0.130234	0.134894	0.088252	0.153287*
MAY	0.076413	0.109398	0.015222	0.116251	0.082204	0.005155	0.118073	0.085486	0.022401	-0.226822	-0.100333	0.047317	-0.049258	-0.004981	0.070931
JUNE	0.071158	0.064709	0.089914	0.129232	0.13331*	0.238973	0.133234	0.187352	0.105493	-0.199383	0.152635*	0.020081	0.114335	0.075822	0.120641
JULY	0.013359	0.167678	0.256675	0.081367	0.130621*	0.37360**	1.02989***	0.256165**	0.104209	0.094719	0.171798*	0.032669	0.064362	0.053599	0.116607
AUGUST	-0.021564	0.070507	0.280172*	0.037894	0.065334	0.149019	0.193684	0.153749	0.112091	0.025003	0.039828	0.090639	-0.132794	-0.079577	0.101386
SEPT	0.02269	0.25296**	0.192603	0.025241	-0.001593	0.114235	0.115157	0.168468	0.050895	-0.109752	-0.021225	-0.049195	-0.0172	0.129582	0.098081
OCT	-0.011202	0.092611	-0.177405	0.135315	-0.052071	-0.074064	0.049831	0.137491	0.180448	-0.293514	-0.025386	0.038768	0.241088	0.118774	-0.012224
NOV	-0.039704	0.158415	0.112301	0.176219*	0.036319	0.132028	0.167108	0.189639	0.122164	0.02338	-0.060052	0.095739	0.192098	0.020948	0.136796*
DEC	-0.023959	0.105622	0.154656	0.070608	0.034569	0.068648	0.26126	0.159912	0.173014	-0.081595	0.008144	0.050118	0.054385	0.087272	0.197911**
F-statistic	1.22492	1.275661	1.651952*	0.637354	1.406359	1.179426	1.09915	0.641705	0.609185	0.785013	1.966705**	0.373049	1.060763	0.328883	1.231366

Durbin-Watson stat	2.022749	1.959863	1.964889	2.049219	2.029457	2.027359	1.988693	2.015666	2.097417	2.102087	2.025224	2.020862	2.036735	1.88373	1.926132
Half-Year Effect															
C	-0.07445**	-0.086089***	-0.146058***	-0.057453*	-0.030135	-0.075563	-0.070302	-0.214961***	-0.152724***	-0.113266*	-0.106334***	-0.066647*	-0.197024***	-0.155792***	-0.048546**
SECOND_HALF_YEAR	-0.028781	0.064015	0.061761	0.014072	-0.048304	0.013899	0.228483	0.091001*	0.040592	0.007996	-0.009383	0.011407	0.03813	0.023554	0.032471
F-statistic	0.488882	2.044237	0.892146	0.115896	2.197796	0.051183	2.213529	2.882493	0.56108	0.009839	0.062721	0.048035	0.343404	0.146845	1.035923
Prob(F-statistic)	0.484476	0.152848	0.345169	0.733551	0.1383	0.821072	0.136865	0.089643	0.45388	0.92101	0.802261	0.82654	0.55791	0.701592	0.308806
Durbin-Watson stat	2.014133	1.954441	1.922259	2.045544	2.022236	1.996807	1.98795	2.013556	2.09304	2.078906	2.011548	2.017404	2.031066	1.88207	1.922516
Half-Month Effect															
C	-0.062648**	-0.031009	-0.110797**	-0.040911	-0.068811***	-0.083225*	0.110102	-0.13213***	-0.094342**	-0.096869*	-0.117329***	-0.038322	-0.142606***	-0.080583*	-0.011468
SECOND_HALF_MONTH	-0.051982	-0.043141	-0.000782	-0.018361	0.027921	0.030292	-0.123842	-0.07096	-0.073633	-0.023213	0.012248	-0.04381	-0.068849	-0.123177**	-0.040595
F-statistic	1.595584	0.928582	0.000145	0.197285	0.733767	0.24714	0.650184	1.752286	1.847242	0.084288	0.106843	0.709062	1.119532	4.023968	1.618617
Prob(F-statistic)	0.20662	0.33528	0.990384	0.656952	0.391725	0.619227	0.420083	0.185682	0.174198	0.77164	0.743787	0.399848	0.290094	0.044933	0.203326
Durbin-Watson stat	2.014486	1.95404	1.920835	2.045205	2.021247	1.996156	1.987919	2.012581	2.093062	2.079106	2.011407	2.017523	2.031062	1.883462	1.922515
Turn-of-the-Month Effect															

C	-0.09776***	-0.071953***	-0.15254***	-0.050037**	-0.056591***	-0.079254**	-0.05401	-0.205948***	-0.184231***	-0.119815***	-0.136535***	0.097721***	-0.203446***	-0.217396***	-0.05721***
TOM	0.044004	0.09705*	0.211248***	-0.001279	0.010417	0.060049	0.518577***	0.192968***	0.26846***	0.057577	0.13063***	0.063349	0.131898	0.379666***	0.129256***
F-statistic	0.717466	2.945811*	6.729098***	0.000601	0.064118	0.603559	7.153892***	8.149627***	15.47688***	0.322218	7.647288***	1.973934	2.580841	24.10033***	10.26499***
Durbin-Watson stat	2.014194	1.953912	1.928803	2.045469	2.021129	1.997003	1.991225	2.018583	2.103462	2.080269	2.014032	2.100069	2.032184	1.894717	1.925162
Turn-of-the-Year Effect															
C	-0.090078***	-0.054054**	-0.127167***	-0.046184**	-0.054061***	-0.07561**	0.048389	-0.17135***	-0.135394***	-0.124096***	-0.115613***	-0.062903**	-0.172559***	-0.151016***	-0.03862**
TOY	0.014027	0.015773	0.243324*	-0.067661	-0.008307	0.120253	-0.026021	0.04717	0.054529	0.233779	0.075198	0.035485	-0.08597	0.119715	0.106634
F-statistic	0.027593	0.028412	3.464778*	0.610641	0.014722	0.956743	0.006599	0.18391	0.240616	2.103302	0.913373	0.105536	0.395707	0.886568	2.535047
Durbin-Watson stat	2.013793	1.953467	1.926651	2.045599	2.021045	1.998392	1.988184	2.012057	2.092776	2.083648	2.01193	2.017539	2.031003	1.882736	1.922564
Week-of-the-Month Effect															
C	-0.086679*	-0.031543	-0.039153	-0.022716	-0.0899**	-0.126103	0.447111**	-0.032691	0.0487	-0.120146	-0.103151**	-0.034328	-0.091126	0.066416	0.053477

SECOND WEEK	0.045808	-0.03174	-0.127241	-0.024517	0.031958	0.060752	-0.529382**	-0.112711	-0.196303**	0.061981	-0.022312	0.035067	-0.102294	-0.179493*	-0.097396*
THIRD_WEEK	-0.017473	-0.012154	-0.145794	-0.035616	0.051201	-0.047382	-0.50573**	-0.228785***	-0.263763***	-0.074652	-0.073452	-0.089893	-0.074779	-0.306925***	-0.125547**
FOURTH_WEEK	-0.063553	-0.078367	-0.168546	-0.081591	-0.038271	0.093483	-0.495897**	-0.22506***	-0.29453***	-0.087102	-0.028251	-0.098879	-0.186447*	-0.37337***	-0.131286**
FIFTH_WEEK	0.036873	0.045515	0.20005*	0.034287	0.168544***	0.218739**	-0.318163	-0.035584	-0.045452	0.225044	0.138226**	0.058763	-0.017983	-0.081721	-0.027209
F-statistic	0.995415	0.765519	3.89120***	0.807825	3.91662***	1.965991*	1.491603	2.920853**	4.29402***	1.806321	3.075549**	1.559804	1.012128	4.79561***	2.515176**
Durbin-Watson stat	2.016	1.954	1.925	2.046	2.026	2.005	1.987	2.019	2.104	2.085	2.018	2.021	2.033	1.893	1.924

Note: '***', '**', '*' indicates significant at 1%, 5% and 10% respectively.

Augmented Dickey-Fuller test statistic for size based indices return series

Index	t-Statistic
Nifty100	-57.80301***
Nifty Midcap150	-54.15882***
Nifty Smallcap 250	-49.94992***

Note: '***' indicates significant at 1%.

Dummy Variable Regression coefficients for size-based indices return series

	Nifty100	Nifty Midcap150	Nifty Smallcap 250
Day-of-the-Week Effect			
C	-0.028615	-0.016986	0.065961
TUESDAY	0.125426**	0.102658	-0.01822
WED	0.089664	0.109603*	0.007407
THUR	0.035222	0.053836	-0.019202
FRI	0.094445*	0.082835	-0.079723
F-statistic	1.592533	0.997403	0.46141
Durbin-Watson stat	1.966255	1.837701	1.679076
Month-of-the-Year Effect			
C	-0.000626	-0.007082	-0.046474
FEB	-0.044746	-0.052438	-0.056204
MARCH	0.026708	0.017695	0.036679
APRIL	0.108407	0.176846*	0.232149**
MAY	0.044989	0.031174	0.071337
JUNE	0.072943	0.099928	0.150573
JULY	0.103185	0.103689	0.105766
AUGUST	-0.003516	0.036771	0.027952
SEPT	0.025372	0.052107	0.066656
OCT	0.082688	0.083802	0.189922*
NOV	0.040223	0.092242	0.100708

DEC	0.036593	0.083521	0.171068
F-statistic	0.527781	0.709027	1.132673
Durbin-Watson stat	1.971284	1.842081	1.684963
Half-Year Effect			
C	0.033554	0.037089	0.024398
SECOND_HALF_YEAR	0.013536	0.031319	0.039258
F-statistic	0.143278	0.613816	0.760983
Durbin-Watson stat	1.968622	1.838977	1.679613
Half-Month Effect			
C	0.0508**	0.08142***	0.028252
SECOND_HALF_MONTH	-0.02046	-0.056018	0.031127
F-statistic	0.327218	1.96373	0.478168
Durbin-Watson stat	1.96832	1.839219	1.678623
Turn-of-the-Month Effect			
C	0.019238	0.003502	0.005669
TOM	0.109606**	0.256008***	0.199624***
F-statistic	5.855412**	25.70771***	12.2849***
Durbin-Watson stat	1.972202	1.851858	1.687313
Turn-of-the-Year Effect			
C	0.039432**	0.048316**	0.029093
TOY	0.015241	0.074249	0.247199***
F-statistic	0.041525	0.78869	6.909724***
Durbin-Watson stat	1.968558	1.839226	1.681613
Week-of-the-Month Effect			
C	0.08958**	0.177377***	0.099946*
SECOND WEEK	-0.069052	-0.143323**	-0.092625
THIRD_WEEK	-0.069553	-0.189914***	-0.200424***

FOURTH_WEEK	-0.101913*	-0.225692***	-0.092731
FIFTH_WEEK	0.041557	0.029365	0.222933***
F-statistic	1.525056	5.912961***	8.658734***
Durbin-Watson stat	1.972854	1.852062	1.690624

Note: '***', '**', '*' indicates significant at 1%, 5% and 10% respectively.

Augmented Dickey-Fuller test statistic for select emerging market indices return series

Index	t-Statistic
Brazil (Bovespa)	-79.80097***
China (Shanghai Composite Index)	-74.77893***
India (Nifty50)	-73.40904***
Indonesia (Jakarta Stock Exchange)	-69.65135***
Mexico (BMV IPC)	-72.49755***
Russia (MOEX)	-77.26118***
Turkey (BIST 100)	-77.23751***

Note: '***' indicates significant at 1%.

Dummy Variable Regression coefficients for select emerging market indices return series

	Brazil (Bovespa)	China (Shanghai Composite Index)	India (Nifty50)	Indonesia (Jakarta Stock Exchange)	Mexico (BMV IPC)	Russia (MOEX)	Turkey (BIST 100)
Day-of-the-Week Effect							
C	-0.006683	0.041748	0.057825**	-0.102395***	0.053918**	0.150027***	0.128219***
TUESDAY	0.033756	0.018254	0.013102	0.166366***	-0.04169	-0.095359**	-0.104908*
WED	0.103354**	-0.060619	-0.00799	0.233648***	-0.016344	-0.079281*	-0.087923
THUR	0.011552	-0.117419***	-0.017146	0.150389***	-0.056698	-0.134676***	0.047593
FRI	0.035123	-0.038931	0.003014	0.192595***	-0.031066	-0.075776	-0.018853
Variance Equation							
C	0.055207***	0.020738***	0.032255***	0.035029***	0.023645***	0.040352***	0.085296***
RESID(-1)^2	0.023809***	0.073618***	0.055012***	0.080854***	0.018087***	0.079412***	0.067408***
RESID(-1)^2*(RESID(-1)<0)	0.087706***	0.026031***	0.111996***	0.073136***	0.105898***	0.070987***	0.060862***

GARCH(-1)	0.910067***	0.907423***	0.870507***	0.862156***	0.910067***	0.87801***	0.878781***
Durbin-Watson stat	2.062975	1.96107	1.902711	1.813536	1.854929	1.996929	1.990855
F-statistic	5.593357**	0.012107	0.016033	0.843785	0.024225	1.088569	0.075685
Obs*R-squared	5.589979**	0.012111	0.016039	0.843952	0.024233	1.088735	0.07571
Month-of-the-Year Effect							
C	0.078913	0.078523*	0.027836	0.035861	0.052585	0.152009***	0.197009***
FEB	-0.082927	0.007666	-0.033069	0.034154	-0.115643**	0.065306	-0.194861**
MARCH	-0.10123	-0.098729	0.04098	0.019053	0.035187	-0.15358**	-0.152539*
APRIL	-0.057292	-0.067219	0.002519	0.057313	-0.037606	-0.047348	-0.072339
MAY	-0.144709*	-0.090385	0.090026*	-0.069077	-0.063165	-0.167481**	-0.190685**
JUNE	-0.16683**	-0.116524*	-0.010436	-0.016186	-0.080674	-0.122405	-0.176647*
JULY	0.013298	-0.09625	0.042034	0.089214	-0.044797	-0.114826	-0.018655
AUGUST	-0.041024	-0.112739*	0.025638	-0.062382	-0.080326	-0.102654	-0.18214*
SEPT	-0.018166	-0.10239*	0.066868	0.008097	-0.049508	-0.075407	-0.093669
OCT	-0.007921	-0.080648	0.00117	0.000581	0.001423	-0.102504	-0.01297
NOV	-0.03494	-0.051494	0.087022	-0.048926	0.020757	-0.104642	-0.097746
DEC	0.03453	-0.065227	0.018345		0.076232	-0.03973	-0.047069
Variance Equation							
C	0.052959***	0.020721***	0.032643***	0.032453***	0.023558***	0.038465***	0.084403***
RESID(-1)^2	0.021987***	0.072695***	0.05433***	0.075931***	0.015767***	0.078125***	0.066511***
RESID(-1)^2*(RESID(-1)<0)	0.089556***	0.028165***	0.115314***	0.070877***	0.110357***	0.073481***	0.061108***
GARCH(-1)	0.911998***	0.907292***	0.869327***	0.869687***	0.910286***	0.878878***	0.87977***
Durbin-Watson stat	2.064102	1.961929	1.903353	1.818	1.857724	1.995939	1.994569
F-statistic	5.583754**	0.025673	0.020614	0.581981	0.003246	1.325271	0.095292
Obs*R-squared	5.58039**	0.025682	0.020621	0.582123	0.003247	1.325421	0.095322

Half-Year Effect							
C	-0.01369	0.010891	0.04271**	0.042149**	0.011045	0.083574***	0.065762**
SECOND_HALF_YEAR	0.084008**	-0.016899	0.024936	0.006626	0.026205	-0.022504	0.056619
Variance Equation							
C	0.054157***	0.020666***	0.032312***	0.034629***	0.023628***	0.040011***	0.086157***
RESID(-1)^2	0.024079***	0.073321***	0.054848***	0.07816***	0.017952***	0.079302***	0.067083***
RESID(-1)^2*(RESID(-1)<0)	0.086914***	0.026398***	0.112278***	0.070078***	0.105189***	0.069504***	0.060923***
GARCH(-1)	0.910708***	0.90756***	0.870513***	0.866247***	0.910523***	0.878865***	0.878759***
Durbin-Watson stat	2.063564	1.96062	1.90394	1.815448	1.854737	1.997198	1.991387
F-statistic	5.27892**	0.033961	0.022315	0.632599	0.014711	1.159783	0.062443
Obs*R-squared	5.27601**	0.033973	0.022322	0.632747	0.014716	1.159946	0.062463
Half-Month Effect							
C	0.050889**	0.048198**	0.063717***	0.045909***	0.0263	0.089713***	0.084263***
SECOND_HALF_MONTH	-0.040407	-0.087735***	-0.015358	-0.000713	-0.003232	-0.035085	0.021838
Variance Equation							
C	0.054933***	0.02053***	0.032367***	0.034581***	0.023874***	0.040472***	0.086057***
RESID(-1)^2	0.023838***	0.073203***	0.054725***	0.078116***	0.018359***	0.079432***	0.067267***
RESID(-1)^2*(RESID(-1)<0)	0.087399***	0.02646***	0.112493***	0.070066***	0.105406***	0.069901***	0.061236***
GARCH(-1)	0.910288***	0.9077***	0.870461***	0.866329***	0.909802***	0.878391***	0.878503***
Durbin-Watson stat	2.06243	1.962531	1.903159	1.815445	1.854574	1.997143	1.990223
F-statistic	5.364454**	0.049796	0.014218	0.631566	0.01556	1.139194	168.9324***
Obs*R-squared	5.36142**	0.049812	0.014223	0.631714	0.015565	1.139358	164.3729***

Turn-of-the-Month Effect							
C	0.001482	-0.040701***	0.039391***	0.034852**	0.010187	0.042748**	0.077147***
TOM	0.148657***	0.213473***	0.089005***	0.055412**	0.078373***	0.156248***	0.096406**
Variance Equation							
C	0.055571***	0.02112***	0.032509***	0.035101***	0.024017***	0.040352***	0.086607***
RESID(-1)^2	0.02372***	0.074644***	0.055843***	0.077868***	0.018734***	0.079568***	0.067536***
RESID(-1)^2*(RESID(-1)<0)	0.088238***	0.026508***	0.111286***	0.070922***	0.104686***	0.070446***	0.061492***
GARCH(-1)	0.909659***	0.90603***	0.869874***	0.865677***	0.909494***	0.878025***	0.877941***
Durbin-Watson stat	2.065982	1.965216	1.906481	1.817463	1.857437	2.000718	1.992885
F-statistic	5.481395**	0.076212	0.015915	0.547356	0.014723	1.192099	0.04692
Obs*R-squared	5.478187**	0.076238	0.01592	0.547492	0.014728	1.192261	0.046935
Turn-of-the-Year Effect							
C	0.019926	-0.003729	0.056162***	0.040474***	0.016811	0.061479***	0.087239***
TOY	0.183395**	0.088704	-0.003976	0.088397*	0.120538***	0.181475***	0.124754
Variance Equation							
C	0.054712***	0.02068***	0.032338***	0.034614***	0.023619***	0.039894***	0.085743***
RESID(-1)^2	0.022959***	0.072846***	0.054758***	0.07825***	0.017884***	0.078329***	0.06741***
RESID(-1)^2*(RESID(-1)<0)	0.08936***	0.027466***	0.112387***	0.070115***	0.106836***	0.072894***	0.06105***
GARCH(-1)	0.910396***	0.907508***	0.870489***	0.86617***	0.909952***	0.878443***	0.878593***
Durbin-Watson stat	2.064328	1.960987	1.903129	1.816451	1.855201	1.999238	1.990501
F-statistic	5.502028**	0.041971	0.011563	0.655758	0.028158	1.269846	0.084311
Obs*R-squared	5.498788**	0.041985	0.011567	0.655909	0.028167	1.270001	0.084338

Week-of-the-Month Effect							
C	0.184667***	0.122484***	0.092459***	0.118641***	0.119788***	0.183886***	0.138153***
SECOND WEEK	-0.217042***	-0.089067**	-0.058293	-0.121594***	-0.159927***	-0.10942**	-0.09962
THIRD_WEEK	-0.126094**	-0.173854***	-0.045145	-0.046929	-0.080562**	-0.162775***	0.014901
FOURTH_WEEK	-0.190925***	-0.149929***	-0.063517	-0.079025**	-0.092227***	-0.117404***	-0.085862
FIFTH_WEEK	-0.20559***	-0.147058***	0.013302	-0.104581**	-0.116144***	-0.13854**	-0.023319
Variance Equation							
C	0.055423***	0.020502***	0.032106***	0.034556***	0.023253***	0.040508***	0.087284***
RESID(-1)^2	0.023732***	0.073462***	0.054999***	0.078715***	0.018488***	0.079746***	0.067836***
RESID(-1)^2*(RESID(-1)<0)	0.087635***	0.026995***	0.111033***	0.069834***	0.103882***	0.070673***	0.062694***
GARCH(-1)	0.909886***	0.907277***	0.871006***	0.865857***	0.910792***	0.87777***	0.876931***
Durbin-Watson stat	2.062478	1.964237	1.905846	1.817108	1.855516	1.998102	1.991244
F-statistic	5.321515**	0.081668	0.000291	0.521097	0.003664	1.117586	0.046174
Obs*R-squared	5.318543**	0.081695	0.000291	0.521229	0.003666	1.117751	0.046189

Note: '***', '**', '*' indicates significant at 1%, 5% and 10% respectively. Here the mentioned F-Statistic is of Heteroskedasticity Test.

Augmented Dickey-Fuller test statistic for foreign exchange return series

Exchange Rate	t-Statistic
USD	-36.02906***
EUR	-76.35114***
GBP	-74.54352***
JYP	-78.20099***

Note: '***' indicates significant at 1%.

Dummy Variable Regression coefficients for select foreign exchange return series

	USD/INR	EUR/INR	GBP/INR	JYP/INR
Sample: 2/01/2001 31/12/2024				
C	-0.0000388	-0.000284	-0.000365**	-0.0000572
TUESDAY	0.000648***	0.000829***	0.000852***	0.00053*
WED	0.000179	0.000654***	0.000598**	0.000263
THUR	0.0000776	0.000471*	0.000586**	0.0000998
FRI	-0.000193	0.0000654	0.000152	-0.00036
F-statistic	7.230086***	4.236238***	3.772929***	2.192359*
Durbin-Watson stat	1.990221	2.004665	1.957656	2.053806
Sample: 2/01/2001 31/12/2006				
C	-0.000182	0.0000532	0.0000056	-0.000153
TUESDAY	0.000456***	-0.0000074	-0.000103	0.000499
WED	0.000016	0.000726	0.000414	0.000713
THUR	0.000156	-0.000549	-0.000133	-0.000335
FRI	0.0000979	0.000541	0.000558	-0.000425
F-statistic	2.205797*	1.896328	1.077717	2.048035*
Durbin-Watson stat	1.945202	2.150862	1.983413	2.167947
Sample: 1/01/2009 31/12/2014				
C	-0.000321	-0.001059***	-0.000716*	-0.000761

TUESDAY	0.00145***	0.002038***	0.001851***	0.002227***
WED	0.000686	0.001574***	0.001165**	0.001172
THUR	0.000518	0.001326**	0.00109*	0.00044
FRI	-0.000148	0.000763	0.000644	-0.000123
F-statistic	3.452361***	4.280615***	2.996425**	3.333754***
Durbin-Watson stat	2.000192	1.853669	1.887438	2.03316
Sample: 1/01/2015 31/12/2019				
C	0.000319	0.00000133	-0.000431	0.000829**
TUESDAY	0.000249	0.000561	0.000846	-0.000546
WED	-0.000206	-0.000067	0.000245	-0.000963*
THUR	-0.00046	0.000359	0.001069*	-0.000307
FRI	-0.000691**	-0.000718	-0.000239	-0.001436**
F-statistic	3.091758**	1.870717	1.973423*	1.857967
Durbin-Watson stat	2.0155	1.928621	1.910677	2.030155
Sample: 1/01/2021 31/12/2024				
C	0.000247	-0.000289	-0.000185	-0.000367
TUESDAY	0.0000239	0.000596	0.000806	-0.000655
WED	0.000103	0.0000827	0.000202	-0.000058
THUR	-0.000315	0.000869**	0.000435	0.000879
FRI	-0.00022	-0.000166	-0.000138	0.00033
F-statistic	1.047005	2.024612*	1.049115	1.59278
Durbin-Watson stat	1.987958	1.994352	1.965034	1.983921
Sample: 2/01/2001 31/12/2024				
C	-0.00016	-0.000538**	-0.0000199	-0.0000497
FEB	0.000331	0.000572	-0.000105	-0.0000885
MARCH	-0.0000242	0.000402	-0.000406	-0.000476
APRIL	0.000243	0.000924**	0.000664	-0.0000808
MAY	0.00061**	0.000762**	0.000359	0.000484

JUNE	0.000393	0.000829**	0.000194	0.00018
JULY	0.000135	0.000713*	0.000214	0.000311
AUGUST	0.000748***	0.001081***	0.000283	0.000977**
SEPT	0.000147	0.000545	-0.000114	-0.0000737
OCT	0.000203	0.000457	0.0000102	-0.000177
NOV	0.000468*	0.000784**	0.000299	0.000323
DEC	-0.000054	0.000867**	-0.000209	-0.000235
F-statistic	1.989419**	1.127374	1.039224	1.275274
Durbin-Watson stat	1.998705	2.009949	1.961247	2.058446
Sample: 2/01/2001 31/12/2006				
C	-0.000224	-0.000648	-0.00021	-0.000512
FEB	0.000333	0.000683	0.0000863	0.000392
MARCH	-0.000101	-0.0000403	-0.00048	-0.000288
APRIL	0.000539*	0.001759**	0.001082	0.001107
MAY	0.000676**	0.001581**	0.001119*	0.001564**
JUNE	0.0000923	0.0002	-0.0000693	-0.00000478
JULY	0.000305	0.000899	0.000387	0.000194
AUGUST	0.000232	0.000875	0.000339	0.001211
SEPT	0.000179	0.000891	0.000513	0.000394
OCT	0.000062	0.000899	0.000398	0.000467
NOV	0.000294	0.001268	0.000382	0.000556
DEC	-0.000294	0.001228	0.00065	-0.000099
F-statistic	1.932734**	1.002497	0.913035	1.10918
Durbin-Watson stat	1.969271	2.169225	1.995914	2.180059
Sample: 1/01/2009 31/12/2014				
C	-0.000465	-0.001031*	-0.000353	-0.000345
FEB	0.000482	0.000812	-0.0000906	-0.000904
MARCH	0.000399	0.001159	0.000145	-0.000572

APRIL	0.000379	0.001443*	0.001555*	0.000268
MAY	0.001183	0.000688	0.000668	0.001249
JUNE	0.001086	0.00189**	0.001603*	0.001522
JULY	0.000521	0.001255	0.000683	0.000965
AUGUST	0.001776**	0.002287***	0.001461*	0.002069*
SEPT	-0.000359	0.000603	-0.000375	-0.000476
OCT	0.000198	0.001371	0.000316	-0.000428
NOV	0.001505**	0.001181	0.000999	0.000481
DEC	0.000594	0.000728	0.000162	-0.000416
F-statistic	1.38208	1.07512	1.196603	1.321338
Durbin-Watson stat	2.025641	1.880349	1.91367	2.053213
Sample: 1/01/2015 31/12/2019				
C	0.0000908	-0.00000676	0.000507	0.000969
FEB	0.000121	-0.00028	-0.000581	-0.000107
MARCH	-0.000887*	-0.000744	-0.001355	-0.001594*
APRIL	0.000412	0.000767	0.000739	-0.000231
MAY	0.000172	-0.000168	-0.000992	-0.001153
JUNE	0.0000303	0.000655	-0.000976	-0.00011
JULY	-0.000232	-0.000188	-0.001143	-0.001328
AUGUST	0.000979**	0.001358*	0.000166	0.00061
SEPT	0.0000611	0.00000996	-0.000116	-0.001057
OCT	-0.0000124	-0.000612	-0.000906	-0.001518*
NOV	-0.000132	-0.000573	-0.000235	-0.001846**
DEC	-0.000365	0.00024	-0.001007	-0.001106
F-statistic	1.848956**	1.257157	1.04765	1.503571
Durbin-Watson stat	2.051632	1.951977	1.931661	2.058681
Sample: 1/01/2021 31/12/2024				
C	-0.0000715	-0.000495	0.000145	-0.000621

FEB	0.000299	0.000496	-0.0000693	-0.000116
MARCH	0.0002	0.000508	-0.000119	-0.000268
APRIL	0.000237	0.00031	-0.000466	-0.000692
MAY	0.000119	0.000615	0.000294	0.000432
JUNE	0.000492	0.000374	-0.000292	-0.000516
JULY	0.000219	0.000646	0.000542	0.00199**
AUGUST	-0.00000539	0.000269	-0.000684	0.000291
SEPT	0.000569	0.000271	-0.000832	0.000425
OCT	0.000369	0.000685	0.000477	-0.000625
NOV	0.0000733	0.00072	0.000161	0.002015**
DEC	0.000239	0.000902	0.000152	0.001091
F-statistic	0.44963	0.272324	0.59545	1.809154**
Durbin-Watson stat	2.001748	2.010351	1.982702	2.017594
Sample: 2/01/2001 31/12/2024				
C	0.0000995	0.000036	0.0000901	-0.0000393
SECOND_HALF_YEAR	0.0000103	0.000169	-0.0000303	0.000178
F-statistic	0.009606	1.15456	0.035182	0.806001
Durbin-Watson stat	1.990904	2.005813	1.957652	2.053703
Sample: 2/01/2001 31/12/2006				
C	0.000025	0.0000216	0.0000643	-0.0000642
SECOND_HALF_YEAR	-0.000121	0.000337	0.000172	0.00000289
F-statistic	1.185599	1.051046	0.394202	0.0000846
Durbin-Watson stat	1.953875	2.15698	1.986533	2.163514
Sample: 1/01/2009 31/12/2014				
C	0.000135	-0.0000376	0.00029	-0.0000501
SECOND_HALF_YEAR	0.0000992	0.00024	-0.000104	0.0000781
F-statistic	0.104297	0.488785	0.085584	0.026472
Durbin-Watson stat	2.003408	1.863262	1.89454	2.034023

Sample: 1/01/2015 31/12/2019				
C	0.0000584	0.0000245	-0.0000454	0.000429
SECOND_HALF_YEAR	0.0000788	0.0000117	0.00000275	-0.000499
F-statistic	0.174332	0.001343	0.00006	1.833932
Durbin-Watson stat	2.014509	1.930163	1.91857	2.033062
Sample: 1/01/2021 31/12/2024				
C	0.000155	-0.000109	0.000042	-0.000808***
SECOND_HALF_YEAR	0.0000188	0.000198	0.0000724	0.00106***
F-statistic	0.014679	0.513211	0.049004	7.011208***
Durbin-Watson stat	1.988926	2.004118	1.96838	1.994452
Sample: 2/01/2001 31/12/2024				
C	0.000118	0.000102	-0.000000843	-0.0000477
SECOND_HALF_MONTH	-0.0000261	0.000039	0.000148	0.000194
F-statistic	0.062135	0.061403	0.840967	0.95493
Durbin-Watson stat	1.990894	2.00552	1.958131	2.052835
Sample: 2/01/2001 31/12/2006				
C	-0.0000171	0.000256	0.0000829	-0.00032
SECOND_HALF_MONTH	-0.0000381	-0.000122	0.000134	0.000501
F-statistic	0.117041	0.137881	0.23884	2.53965
Durbin-Watson stat	1.951803	2.156024	1.986982	2.163086
Sample: 1/01/2009 31/12/2014				
C	0.0000948	-0.000158	0.0000809	-0.000259
SECOND_HALF_MONTH	0.000178	0.000476	0.000307	0.000488
F-statistic	0.336179	1.924717	0.74023	1.035581
Durbin-Watson stat	2.004613	1.867115	1.896057	2.034688
Sample: 1/01/2015 31/12/2019				
C	0.0000806	0.000134	0.00000362	0.000153
SECOND_HALF_MONTH	0.0000341	-0.000204	-0.0000936	0.0000496

F-statistic	0.032609	0.405959	0.069561	0.018119
Durbin-Watson stat	2.013715	1.932203	1.918637	2.029836
Sample: 1/01/2021 31/12/2024				
C	0.000268**	0.0000707	0.000189	-0.0000861
SECOND_HALF_MONTH	-0.000204	-0.000157	-0.000218	-0.000358
F-statistic	1.740385	0.322454	0.443895	0.794169
Durbin-Watson stat	1.99307	2.004514	1.969601	1.981882
Sample: 2/01/2001 31/12/2024				
C	0.000199***	0.000201**	0.00015*	0.000145
TOM	-0.000477***	-0.0004**	-0.000381*	-0.000475*
F-statistic	13.29458***	4.10938**	3.530436*	3.656526*
Durbin-Watson stat	1.99593	2.008005	1.959282	2.05616
Sample: 2/01/2001 31/12/2006				
C	0.0000317	0.000132	0.000105	-0.0000169
TOM	-0.000346**	0.00031	0.000236	-0.000233
F-statistic	6.145965**	0.562874	0.474268	0.346812
Durbin-Watson stat	1.960643	2.155585	1.986449	2.166448
Sample: 1/01/2009 31/12/2014				
C	0.000408**	0.000303	0.00034*	0.00035
TOM	-0.001117***	-0.001099**	-0.000517	-0.001802***
F-statistic	8.493791***	6.589655**	1.342455	9.074143***
Durbin-Watson stat	2.017955	1.876568	1.898396	2.052314
Sample: 1/01/2015 31/12/2019				
C	0.000177*	0.0000702	0.000132	0.000252
TOM	-0.000399*	-0.0002	-0.000882**	-0.000371
F-statistic	2.856104*	0.247805	3.95328**	0.64715
Durbin-Watson stat	2.020215	1.930008	1.921207	2.030942
Sample: 1/01/2021 31/12/2024				

C	0.000161*	0.000027	0.000115	-0.000441**
TOM	0.0000192	-0.000177	-0.000183	0.000879*
F-statistic	0.009778	0.261308	0.19939	3.065893*
Durbin-Watson stat	1.989016	2.004217	1.96949	1.981983
Sample: 2/01/2001 31/12/2024				
C	0.000119**	0.00014*	0.000102	0.0000767
TOY	-0.000233	-0.000299	-0.000435	-0.000416
F-statistic	1.158062	0.836612	1.678366	1.020483
Durbin-Watson stat	1.991675	2.005918	1.95852	2.053627
Sample: 2/01/2001 31/12/2006				
C	-0.0000233	0.000179	0.000177	-0.0000128
TOY	-0.000216	0.000225	-0.000407	-0.000811
F-statistic	0.871913	0.108169	0.513385	1.539521
Durbin-Watson stat	1.954579	2.155879	1.987234	2.164296
Sample: 1/01/2009 31/12/2014				
C	0.000206	0.000152	0.00024	0.0000722
TOY	-0.000343	-0.001116	-0.0000451	-0.001344
F-statistic	0.284951	2.426554	0.003655	1.800533
Durbin-Watson stat	2.00448	1.868365	1.894646	2.037027
Sample: 1/01/2015 31/12/2019				
C	0.000113	0.0000224	-0.00000897	0.000119
TOY	-0.000244	0.000131	-0.000571	0.000962
F-statistic	0.384861	0.038689	0.597625	1.573964
Durbin-Watson stat	2.01457	1.930327	1.919596	2.034874
Sample: 1/01/2021 31/12/2024				
C	0.000198**	0.0000298	0.000115	-0.000238
TOY	-0.000516	-0.000601	-0.000562	-0.000446
F-statistic	2.630408	1.125268	0.703363	0.292802

Durbin-Watson stat	1.994257	2.002421	1.968439	1.98018
Sample: 2/01/2001 31/12/2024				
C	-0.000223*	-0.000317	-0.000352*	-0.000639**
SECOND WEEK	0.000447***	0.000573**	0.000355	0.000896***
THIRD_WEEK	0.000485***	0.000662**	0.000807***	0.000854***
FOURTH_WEEK	0.000347**	0.000399	0.00033	0.000725**
FIFTH_WEEK	0.000219	0.000418	0.000567*	0.000796**
F-statistic	2.550111**	1.873501	2.605463**	2.380144**
Durbin-Watson stat	1.994951	2.006467	1.960016	2.055454
Sample: 2/01/2001 31/12/2006				
C	-0.000255*	0.000542	0.000541	-0.001106***
SECOND WEEK	0.000347*	-0.00038	-0.000701	0.001279**
THIRD_WEEK	0.00031*	-0.0002	-0.000204	0.001396***
FOURTH_WEEK	0.000209	-0.000514	-0.000485	0.000972*
FIFTH_WEEK	0.000119	-0.000655	-0.000457	0.001367**
F-statistic	1.198321	0.412776	0.770529	2.352746*
Durbin-Watson stat	1.959614	2.156889	1.991149	2.16371
Sample: 1/01/2009 31/12/2014				
C	-0.000389	-0.001186***	-0.000523	-0.00142**
SECOND WEEK	0.000436	0.001373**	0.000844	0.001259
THIRD_WEEK	0.000935*	0.001855***	0.001166**	0.001902**
FOURTH_WEEK	0.000807	0.001533***	0.00061	0.001924**
FIFTH_WEEK	0.000501	0.001169*	0.001059	0.001629*
F-statistic	1.061884	3.044219**	1.178273	1.946648
Durbin-Watson stat	2.009977	1.872245	1.90007	2.043259
Sample: 1/01/2015 31/12/2019				
C	-0.0002	0.00000833	-0.00056	-0.000125
SECOND WEEK	0.00043	0.000222	0.000405	0.000681

THIRD_WEEK	0.000402	0.000245	0.001469**	0.000446
FOURTH_WEEK	0.000392	-0.000482	0.0000254	0.000178
FIFTH_WEEK	0.000104	0.000169	0.000548	0.00000919
F-statistic	0.790948	0.805777	2.436211**	0.510792
Durbin-Watson stat	2.015925	1.935587	1.926138	2.035966
Sample: 1/01/2021 31/12/2024				
C	0.000136	-0.000294	-0.000484	0.0000959
SECOND WEEK	0.000135	0.000542	0.000925*	-0.000141
THIRD_WEEK	0.000122	0.000126	0.000593	-0.000928
FOURTH_WEEK	-0.0000689	0.000363	0.000571	-0.000309
FIFTH_WEEK	-0.000101	0.000302	0.000518	-0.000316
F-statistic	0.394701	0.465717	0.758513	0.654271
Durbin-Watson stat	1.993815	2.00315	1.967907	1.979298

Note: ‘***’, ‘**’, ‘*’ indicates significant at 1%, 5% and 10% respectively.