Calendar Anomalies and Seasonality in Indian Equity Markets: Implications for Inclusive Enterprise and Investor Empowerment

Vinay Munde[1], Dr. Mahesh Kumar[1], Dr. Anil Nagtilak[2]

[1,2] Assistant Professor, School of Business MIT World Peace University, Pune, India

[3]Director at Akemi Business School, Pune

Abstract: ***Financial markets play a pivotal role in supporting enterprise expansion and economic development; however, return-generating mechanisms are often influenced by systematic temporal patterns that challenge the assumption of full market efficiency. This study investigates the existence and changing relevance of selected calendar-based anomalies, namely the day-of-the-week effect, month-of-the-year effect, and holiday effect, within the Indian equity market, focusing on a set of listed companies. Using exclusively secondary data, the research applies econometric and time-series techniques to evaluate return behavior across multiple trading periods and market phases. The analysis reveals that while advancements in market structure, regulation, and information dissemination have weakened several traditional anomalies, certain seasonal patterns continue to exert measurable influence on stock returns. These residual effects hold strategic relevance for both individual and institutional investors and shape portfolio decision-making across short-term and long-term horizons. The findings underscore the importance of investor awareness, financial literacy, and policy interventions aimed at minimizing informational asymmetries and structural inefficiencies. By promoting transparency and informed participation, equity markets can evolve into more inclusive and resilient systems that support enterprise growth and equitable wealth creation in emerging economies such as India, thereby reinforcing the broader agenda of empowerment, equity, and enterprise.***

Keywords: Calendar anomalies, Seasonality, Equity markets, Investor empowerment, financial inclusion

1. Introduction

Financial markets are widely regarded as essential mechanisms for mobilizing capital, enabling enterprise growth, and contributing to long-term economic development. Efficient equity markets channel household savings into productive ventures and thereby create opportunities for both enterprise resilience and investor prosperity. However, despite their central role, financial markets do not always conform to the assumptions of efficiency. The Efficient Market Hypothesis (EMH), articulated by Fama (1970), posits that prices fully reflect all available information and hence abnormal profits cannot be systematically earned. In practice, however, empirical evidence from diverse geographies demonstrates the existence of calendar anomalies—systematic variations in returns that are linked to days of the week, months of the year, or trading periods surrounding public holidays.

The persistence of such anomalies raises important questions. First, they indicate potential market inefficiencies, as investors can gain above-normal returns by timing trades. Second, anomalies may disproportionately disadvantage retail investors, many of whom lack awareness or access to sophisticated trading tools. Third, in emerging economies such as India, where financial inclusion remains a policy priority, the continued existence of anomalies may compromise the goal of equitable participation in capital markets.

The Indian equity market has experienced rapid growth over the past three decades, particularly since the liberalization reforms of 1991 and the establishment of the National Stock Exchange (NSE) in 1994. Technological innovations such as electronic trading platforms, algorithmic systems, and stricter Securities and Exchange Board of India (SEBI) regulations have significantly enhanced transparency and liquidity. Yet, as recent global evidence suggests, even highly developed markets continue to show traces of anomalies, albeit with varying intensity. The Indian case is particularly intriguing because it combines features of rapid modernization with unique socio-cultural dynamics, such as the influence of festivals (e.g., Diwali, Holi) and fiscal cycles (e.g., Union Budget announcements).

This study investigates the persistence of calendar anomalies in the Indian equity market, with a focus on three widely examined patterns: the day-of-the-week effect, the month-of-the-year effect, and the holiday effect. Drawing on secondary data and employing econometric analysis, the research seeks to determine whether these anomalies have diminished over time or continue to influence investor behavior. More importantly, the study situates these findings in the broader discourse of investor empowerment, financial literacy, and inclusive enterprise development.

The objectives of this research are threefold:
1) To examine the presence and evolution of day-of-the-week, month-of-the-year, and holiday anomalies in the Indian equity market.
2) To assess the implications of these anomalies for retail and institutional investors, particularly in terms of strategy, risk, and access.
3) To link the persistence (or decline) of anomalies with policy priorities related to financial inclusion, transparency, and investor education.

By exploring these dimensions, the paper contributes not only to the academic literature on financial anomalies but also to the practical discourse on how markets can serve as inclusive platforms for wealth creation. The findings are particularly relevant in the context of India's growing emphasis on sustainable finance, digital trading ecosystems, and investor protection.

2. Literature Review

2.1 Calendar Anomalies and Market Efficiency

The EMH has been a cornerstone of modern finance, yet it has been repeatedly challenged by empirical evidence of predictable return patterns. Calendar anomalies refer to systematic irregularities in asset returns that correspond to specific time intervals. Early studies such as Cross (1973) and French (1980) documented the day-of-the-week effect in US markets, noting that Mondays often delivered lower returns compared to Fridays. Similarly, Rozeff and Kinney (1976) highlighted the month-of-the-year effect, particularly the "January effect," where small-cap stocks outperformed during the first month of the year. The holiday effect, first studied by Lakonishok and Smidt (1988), revealed abnormal positive returns during trading sessions preceding public holidays.

These anomalies suggest that psychological, institutional, and structural factors influence investor decisions, contradicting the notion of purely rational markets. Behavioral finance scholars such as Thaler (1987) have attributed such patterns to sentiment, overreaction, and cognitive biases. Others have argued that institutional trading practices, settlement systems, and fiscal cycles also contribute to these recurring irregularities.

2.2 Global Evidence

Extensive research across global markets has validated the persistence of anomalies, though with varying intensity. For instance, Kiymaz and Berument (2003) found significant day-of-the-week effects in emerging markets such as Turkey. Studies on Asian economies, including Japan (Jaffe & Westerfield, 1985), Hong Kong (Cheung & Coutts, 1999), and China (Yuan & Gupta, 2014), report similar irregularities, though reforms and globalization have moderated these effects over time. In developed economies like the US and UK, anomalies remain detectable but weaker, suggesting that technological efficiency and regulatory oversight mitigate structural inefficiencies.

More recently, researchers have noted a declining trend in classical anomalies, attributing it to the rise of algorithmic trading, improved disclosure norms, and globalization of capital flows (Lim & Brooks, 2011). However, even as traditional anomalies diminish, new forms of seasonality linked to digital trading behavior, high-frequency strategies, or global risk cycles are emerging, highlighting the evolving nature of financial markets.

2.3 Indian Evidence

Research on Indian equity markets has produced mixed findings. Raj and Kumari (2006) documented the presence of a day-of-the-week effect in the Bombay Stock Exchange (BSE), with significantly negative Monday returns and positive Friday returns. Bhattacharya et al. (2003) observed monthly seasonality, with April and November showing higher abnormal returns, possibly linked to fiscal-year cycles and festival seasons. Similarly, Joshi and Pandya (2008) highlighted the pre-Diwali effect, noting that optimism around the festival often drives stock rallies.

However, more recent studies suggest that anomalies in India are less pronounced post-2010, coinciding with advancements in trading technology and regulatory frameworks. Agarwal and Tandon (2018) found that while the day-of-the-week effect had weakened, the holiday effect persisted in specific sectors. Furthermore, studies examining NSE indices during the COVID-19 pandemic observed heightened volatility, raising questions about whether crises temporarily revive anomaly-like patterns (Kaur & Joshi, 2021).

The Indian context is distinct because anomalies may not solely reflect structural inefficiencies but also cultural and behavioral dimensions. Festivals, budget announcements, and monsoon outcomes often shape investor sentiment, producing cyclical trading patterns not fully explained by Western models.

2.4 Implications for Investor Empowerment and Inclusion

Most anomaly research has been limited to documenting statistical significance, with little emphasis on the social and policy implications. Yet, in emerging economies such as India, the persistence of anomalies carries broader consequences. Retail investors, who often lack sophisticated knowledge or advisory support, may be disadvantaged if anomalies allow informed traders to systematically exploit timing strategies. This can deepen inequalities in access to capital markets, contradicting the objectives of financial inclusion.

Conversely, recognizing these anomalies provides an opportunity for investor education and empowerment. Awareness of seasonal effects can improve decision-making, helping investors align short-term strategies with long-term wealth goals. For policy makers, understanding anomalies offers insights into the need for reforms in disclosure, trading mechanisms, and financial literacy programs.

2.5 Research Gap

+While extensive literature exists on calendar anomalies in both global and Indian contexts, few studies explicitly connect these irregularities to inclusive enterprise and investor empowerment. Most analyses remain technical, focusing on statistical tests without addressing their implications for financial literacy, equitable participation, and sustainable enterprise growth. This study seeks to bridge that gap by linking econometric evidence of anomalies to broader discourses on investor confidence, market fairness, and inclusive economic development.

3. Research Methodology/Approach

3.1 Research Design

This study adopts a quantitative, empirical research design based entirely on secondary data from the Indian equity market. The design is exploratory in identifying the presence of calendar anomalies and explanatory in analyzing their persistence across different time horizons. By employing econometric time-series techniques, the methodology allows for systematic testing of whether stock returns exhibit predictable seasonal patterns.

3.2 Data Source and Sampling

The data set comprises daily and monthly stock returns from selected large-cap companies listed on the National Stock Exchange (NSE) and the BSE Sensex index. The sampling includes companies with continuous trading histories over the past 10–15 years, ensuring reliability and representativeness. Secondary data are drawn from reliable sources such as the NSE database, CMIE ProwessIQ, and Bloomberg/Refinitiv repositories.

3.3 Variables and Return Computation

The dependent variable is the daily/periodic stock return, computed as:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$$

where R_t is the return on day t, P_t is the closing price on day t, and P_{t-1} is the closing price on the previous day.

Independent variables are dummy variables representing the calendar effects:

- Day-of-the-week effect: Dummy variables for Monday through Friday.
- Month-of-the-year effect: Dummy variables for each of the 12 months.
- Holiday effect: Dummy variables for days preceding public holidays and post-holiday sessions.

Control variables include market index returns (Nifty/Sensex) to account for systematic market movements.

3.4 Econometric Models

The methodology employs regression-based models to test for anomalies. For instance, the day-of-the-week effect is modeled as:

$$R_t = \alpha + \sum_{i=1}^{4} \beta_i D_i + \epsilon_t$$

where D_i are dummy variables for each trading day (with one day omitted as the baseline).

Similarly, for the month-of-the-year effect:

$$R_t = \alpha + \sum_{j=1}^{11} \gamma_j M_j + \epsilon_t$$

where M_j are dummy variables for each month (with one month omitted as the base).

For the holiday effect, a binary dummy variable H_t is introduced:

$$R_t = \alpha + \delta H_t + \epsilon_t$$

In addition, ARCH/GARCH models are applied to control for volatility clustering and heteroskedasticity, which are common in financial return series.

3.5 Hypothesis Testing

The following hypotheses guide the analysis:

- H1: Daily returns differ significantly across trading days (day-of-the-week effect).
- H2: Monthly returns differ significantly across months (month-of-the-year effect).
- H3: Pre-holiday trading days yield higher abnormal returns compared to non-holiday days (holiday effect).
- H4: The magnitude of anomalies has declined in the post-reform period.

Statistical significance is evaluated using t-tests, F-tests, and Wald chi-square tests. A 5% significance level (α=0.05\alpha = 0.05α=0.05) is adopted.

3.6 Robustness Checks

To ensure robustness, the study compares results across indices (Nifty vs. Sensex) and sectors (e.g., banking, IT, FMCG). Additionally, sub-period analysis tests whether anomalies persist in periods of market stress, such as the Global Financial Crisis (2008) and the COVID-19 pandemic (2020).

4. Data Analysis

4.1 Day of the week effect:

Table 1: Descriptive Statistics by Day of the Week

Groups	count	sum	average	Variance
Monday	1233	77.97285316	0.063238324	1.43285826
Tuesday	1242	98.25206132	0.07910794	1.470558567
Wednesday	1231	30.30122962	0.024615134	1.68919274
Thursday	1240	81.63143922	0.065831806	1.966721005
Friday	1200	6.786286358	0.005655239	2.553560971

(Source: Author's Calculation)

4.1.1 Descriptive Statistics by Day of the Week:

The table 1 presents the summary statistics of Nifty 50 daily returns grouped by weekdays: On Monday, Average return is 0.0632, with variance of 1.43. On Tuesday, it Shows the highest average return (0.0791) among all days, with variance 1.47. On the Wednesday, Returns are relatively low, with an average of 0.0246 and variance 1.69. On the Thursday, mean return of 0.0658, with variance increasing to 1.97 and on the Friday, the lowest average return (0.0056) and the highest variance (2.55), indicating greater uncertainty on the last trading day of the week. Overall, the mean returns across days are close to zero, suggesting no strong day-of-the-week return anomaly. However, dispersion (variance) increases towards the end of the week, especially on Fridays.

Paper ID: SR26302114101 DOI: https://dx.doi.org/10.21275/SR26302114101

4.1.2 Implications for the Day-of-the-Week Effect

The Tuesday effect (highest mean return) and the Friday effect (lowest mean return with highest volatility) are evident in descriptive form. Yet, differences are marginal: Tuesday's mean return is only slightly higher than Monday and Thursday, and statistical tests confirm that these differences are not statistically significant. Hence, the results provide weak evidence of a weekday pattern in returns. For investors, these findings imply that simple timing strategies based on weekdays are unlikely to generate abnormal profits, given the small differences in mean returns and high within-day variance. For market efficiency, the results support the weak-form Efficient Market Hypothesis (EMH): prices in the Indian equity market appear to follow a random pattern without systematic weekday anomalies.

Table 2: Daily ANOVA table

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Days	4	5	1.177	0.647	0.629
Residuals	6141	11166	1.818		

(Source: Author's Calculation)

The ANOVA table2 for daily returns examines whether average returns differ across the 5 trading days considered (e.g., Monday–Friday). The results show: F value = 0.647, p = 0.629, which again exceeds 0.05. This indicates that the differences in average returns across trading days are not statistically significant. The residual variance (Mean Sq = 1.818) is much higher than the variance explained by days (Mean Sq = 1.177), showing that daily effects contribute minimally to total return variability. So, there is no evidence of day-of-the-week effects in returns for this NIFTY 50 data. Returns appear consistent across trading days.

Table 3: Day-of-the-Week ANOVA Results

	Df	SS	MS	F value	Pr(>F)
M	1	0.4	0.35866	0.1972	0.6570
T	1	2.0	2.02984	1.1163	0.2908
W	1	0.1	0.11051	0.0608	0.8053
TH	1	2.2	2.20835	1.2145	0.2705
Residuals	6141	11166.4	1.81834		

(Source: Author's Calculation)

The regression model (Table3) tested whether average returns differ across trading days (Monday through Thursday, with Friday as the baseline). The ANOVA results indicate the following: for all the days (from Monday to Thursday), there is no significant difference in returns compared to Friday.

The residual mean square (1.81834) is much larger than the variance explained by day-of-the-week dummies, indicating that most of the variability in returns is attributable to other factors.

The results of the ANOVA test indicate that returns do not significantly differ across trading days (Monday through Thursday, relative to Friday). This finding suggests that the Day-of-the-Week effect, often documented in global equity markets, is not evident in the NIFTY 50 index.

In line with these evolving findings, the current results support the view that day-of-the-week anomalies may no longer be present in the studied market context, reinforcing the notion that markets may have become more efficient with respect to calendar-based anomalies.

Table 5: Coefficients

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept) (Monday)	0.063238	0.038402	1.647	0.0997.
T	0.015870	0.054210	0.293	0.7697
W	-0.038623	0.054331	-0.711	0.4772
TH	0.002593	0.054232	0.048	0.9619
F	-0.057583	0.054681	-1.053	0.2923

(Source: Author's Calculation)

(Signify. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)
Residual standard error: 1.348 on 6141 degrees of freedom
Multiple R-squared: 0.0004214, Adjusted R-squared: -0.0002297
F-statistic: 0.6472 on 4 and 6141 DF, p-value: 0.6288

The regression model tested (Table5) whether daily stock returns differ systematically across weekdays, with Monday serving as the baseline (intercept).

The intercept (0.0632) represents the average return on Mondays. It is positive but only marginally significant at the 10% level (p = 0.0997).

Thus, H0 (no abnormal Monday return) cannot be rejected at the 5% level, though some weak evidence of a Monday effect exists. Other Weekdays (Relative to Monday)

On Tuesday (T), its coefficient is 0.0159 and p is 0.7697, so it is insignificant; fail to reject H0.

On Wednesday (W), its coefficient is –0.0386 and p is 0.4772, so it is insignificant; fail to reject H0. On Thursday (TH), its coefficient is 0.0026 and p is 0.9619, so it is insignificant; fail to reject H0. On Friday (F), its coefficient is –0.0576 and p is 0.2923, so it is Insignificant; fail to reject H0.

Hence, across all weekdays, H0 (returns are equal to Monday) cannot be rejected, suggesting no statistically significant day-specific anomaly.

About Goodness of Fit, $R^2 = 0.00042$ and Adjusted $R^2 = -0.00023$, so explanatory power of the model is negligible.

F-statistic is 0.6472 (p = 0.6288), this shows the joint null hypothesis (H0: all weekday coefficients are 0) cannot be rejected. The results provide no statistical evidence of a day-of-the-week effect in the Nifty 50 during the study period.

Average Monday returns are weakly positive, but not reliably different from zero.

On other weekdays (Tuesday–Friday) show no significant variation relative to Monday. Overall, we fail to reject all null hypotheses regarding weekday anomalies.

This outcome supports the weak-form Efficient Market Hypothesis (EMH), as predictable weekday patterns do not significantly explain variations in stock returns. For investors, this implies that attempting to exploit weekday timing strategies is unlikely to yield consistent abnormal profits in the Indian equity market.

4.2 Month of the year effect:

Table 6: Descriptive Statistics Month of the year effect

Groups	count	sum	average	Variance
Jan	532	-26.845	-0.050	1.890
Feb	490	-9.97330	-0.02035	1.65540
Mar	508	-6.11008	-0.01203	2.90309
Apr	476	45.82619	0.09627	1.80148
May	530	12.3718	0.0233	2.7340
Jun	526	30.5535	0.0581	1.6575
Jul	543	46.06608	0.08484	1.37538
Aug	513	29.0097245	0.056549171	1.256135209
Sep	509	38.37898019	0.075400747	1.662934209
Oct	502	14.25719495	0.028400787	2.214068477
Nov	493	65.40112486	0.132659482	1.522998836
Dec	526	57.94316695	0.110158112	1.155153941

(Source: Author's Calculation)

The monthly averages and variances of Nifty 50 returns are summarized below: Negative Return Months are January (–0.050), February (–0.020), and March (–0.012). Positive Return Months are April (0.096), July (0.0848), September (0.0754), November (0.1326) is the highest return, and December (0.1101) is the second highest return show notable positive averages. On volatility trends, March (2.90) and May (2.73) exhibit the highest variances, suggesting riskier periods, while December (1.15) and August (1.25) reflect relatively stable return distributions. Overall, the data suggests seasonal variation in returns, with early months (Jan–Mar) showing weakness, while year-end months (Nov–Dec) display strong positive returns.

Possible Calendar Anomalies: January Effect (Negative in India): Unlike developed markets where January often exhibits excess positive returns, Indian markets here reflect a negative January effect. This may be due to profit booking, tax-related adjustments, or investor sentiment at the start of the calendar year. March Effect: Returns in March are weak (–0.012) and highly volatile (2.90), possibly reflecting fiscal year-end adjustments, corporate balance-sheet considerations, and institutional portfolio reshuffling in India. November–December Rally: The strongest returns occur in November (0.133) and December (0.110). This could reflect pre-budget optimism, increased foreign portfolio inflows, and festive season liquidity in the Indian market. July and September Strength: July (0.0848) and September (0.0754) also show consistently strong returns, which may be linked to quarterly earnings announcements and institutional rebalancing.

Table 7: ANOVA Results for Monthly Returns

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FEB	1	2.5	2.5087	1.3799	0.24016
MAR	1	2.5	2.4504	1.3478	0.24570
APR	1	0.7	0.661	0.3636	0.54651
MAY	1	0.7	0.6834	0.3759	0.53984
JUN	1	0.0	0.0069	0.0038	0.95077
JUL	1	0.3	0.3340	0.1837	0.66820
AUG	1	0.0	0.0012	0.0006	0.97968
SEP	1	0.2	0.1877	0.1032	0.74798
OCT	1	0.4	0.4337	0.2385	0.62527
NOV	1	3.6	3.5862	1.9726	0.16022
DEC	1	6.8	6.8235	3.7532	0.05275

Residuals 6136 11155.5 1.8180

(Signify. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)

The ANOVA table from the regression of Return on monthly dummy variables (FEB–DEC) shows the individual contribution of each month to explaining variations in returns. Most months have p-values greater than 0.05, indicating that their individual effect on returns is not statistically significant. This suggests that, for the dataset considered, returns do not systematically differ across these months. December (DEC) has a p-value of 0.05275, which is marginally significant at the 10% level. This indicates a weak tendency for higher returns in December, consistent with a potential "December effect" observed in financial markets.

The residual sum of squares is 11155.5 with 6136 degrees of freedom, giving a residual variance of 1.818. This shows that most of the variation in returns is not explained by monthly effects, implying that other factors (market trends, economic conditions, company-specific events) are likely more important in determining returns.

Table 8: Monthly ANOVA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Months	11	18	1.607	0.884	0.556
Residuals	6136	11155	1.818		

The ANOVA table 8 for monthly returns examines whether average returns differ significantly across the 12 months. The results show: F value = 0.884, p = 0.556, which is much greater than the conventional 0.05 threshold. This indicates that the differences in average returns across months are not statistically significant. The residual variance (Mean Sq = 1.818) is substantially larger than the variance explained by months (Mean Sq = 1.607), suggesting that most of the variability in returns is due to factors other than the month of the year. There is no evidence of monthly seasonality in returns for this dataset. Monthly effects alone do not meaningfully explain variations in returns.

Table 9: Monthly Returns Regression

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.05046	0.05846	-0.863	0.3881
FEB	0.03011	0.08443	0.357	0.7214
MAR	0.03843	0.08364	0.459	0.6459
APR	0.14673	0.08507	1.725	0.0846
MAY	0.07380	0.08275	0.892	0.3725
JUN	0.10855	0.08291	1.309	0.1905
JUL	0.13530	0.08225	1.645	0.1000
AUG	0.10701	0.08343	1.283	0.1997
SEP	0.12586	0.08360	1.506	0.1322
OCT	0.07886	0.08390	0.940	0.3473
NOV	0.18312	0.08429	2.172	0.0299 *
DEC	0.16062	0.08291	1.937	0.0528

(Signify. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)
Residual standard error: 1.348 on 6136 degrees of freedom
Multiple R-squared: 0.001582, Adjusted R-squared: -0.0002078
F-statistic: 0.8839 on 11 and 6136 DF, p-value: 0.5555

The regression model estimates the effect of monthly dummy variables (FEB–DEC) on stock returns, with January as the baseline (intercept). The intercept (-0.05046) represents the average return in January, which is slightly negative but not statistically significant (p = 0.3881). Most monthly coefficients (FEB–OCT) are positive but not significant (p > 0.05), indicating that returns in these months do not differ significantly from January. November shows a statistically significant positive coefficient (0.18312, p = 0.0299), suggesting that returns in November are slightly higher than in January. April (p = 0.0846), July (p = 0.1000), and December (p = 0.0528) are marginally significant at the 10% level, hinting at weakly higher returns in these months.

The model explains very little variation in returns, with R-squared = 0.001582 and an adjusted R-squared slightly negative (-0.0002). This indicates that the monthly dummies alone do not meaningfully explain the variability in returns. The overall F-statistic = 0.8839 (p = 0.5555) confirms that, collectively, the monthly variables are not statistically significant.

4.3 Result

The ANOVA analyses of both monthly and daily returns indicate that calendar-based effects have minimal influence on return variability in this dataset. The monthly ANOVA shows an F value of 0.884 (p = 0.556), indicating that average returns do not differ significantly across months. Similarly, the daily ANOVA reports an F value of 0.647 (p = 0.629), suggesting that returns do not vary significantly across trading days. In both cases, the residual variance far exceeds the variance explained by the time factor (months or days), highlighting that other factors such as macroeconomic conditions, market trends, or firm-specific events are likely the primary drivers of return variability (Plastun, 2020; Kajol, 2020).

These results suggest the absence of strong calendar anomalies, such as monthly seasonality or day-of-the-week effects, for the dataset analyzed. While some studies report phenomena like the “Santa Claus Rally” in December or higher Monday returns in certain markets (Nippani, 2015; Ackert & Athanassakos, 2000), such effects are not evident here, implying that they may be context-dependent and not universally applicable.

Overall, the findings reinforce that calendar-based timing strategies alone are insufficient for predicting stock returns. Researchers and investors should consider integrating additional explanatory variables to better understand return behavior.

The ANOVA analysis of monthly return data reveals that, with the exception of December, no individual month demonstrates a statistically significant effect on returns. This finding suggests that, for the dataset under consideration, monthly fluctuations in returns are largely attributable to factors other than the calendar month.

The marginal significance observed in December, with a p-value of 0.05275, aligns with the concept of the "Santa Claus Rally." This phenomenon refers to the tendency for stock prices to rise during the last five trading days of December and the first two of January. Historically, the S&P 500 has shown positive returns during this period approximately 77% of the time

4.4 Investopedia

The observed pattern in December's returns may be influenced by factors such as increased investor optimism, holiday bonuses, and lower trading volumes, which are characteristic of the holiday season.

However, it's important to note that the statistical significance of December's return is marginal and may not be robust across different datasets or time periods. The absence of significant effects in other months suggests that calendar-based anomalies, while intriguing, may not consistently explain variations in stock returns.

Historically, financial literature has reported systematic return patterns across weekdays. The “Monday effect” (also called the Weekend effect) posits that average returns on Mondays are significantly lower compared to other days (French, 1980; Gibbons & Hess, 1981). Conversely, some studies highlight the Friday effect, where returns tend to be higher at the end of the trading week (Lakonishok & Smidt, 1988). These anomalies challenge the Efficient Market Hypothesis (EMH), as they imply predictable patterns in returns that investors could potentially exploit.

However, more recent studies suggest that such anomalies may have weakened or disappeared over time, possibly due to changes in market microstructure, globalization, and arbitrage opportunities. For instance, Kamath et al. (1998) found that the day-of-the-week effect in Indian markets diminished with liberalization, while more recent work by Plastun et al. (2020) shows that in many emerging markets, the effect remains weak and inconsistent.

Some studies (e.g., Elangovan et al., 2023) documented significant Wednesday effects in Indian markets, while earlier literature in global markets found strong Monday (negative) and Friday (positive) effects. This study results align with Saxena, Purohit & Malhotra (2020), who reported diminishing weekday anomalies in recent Indian data.

The higher Friday volatility could reflect investor repositioning, settlement pressures, or profit booking before weekends, but without statistical significance, these remain interpretive.

The absence of a weekday effect in Indian markets aligns with some studies in emerging economies, where liberalization and technological advances have improved efficiency and eliminated predictable patterns. However, it contrasts with earlier evidence from developed markets such as the U.S., where Monday effects (negative returns) and Friday effects (positive returns) were historically documented.

This divergence may reflect the increasing efficiency of the Indian market, enhanced participation of institutional investors, and global integration, which together reduce opportunities for simple arbitrage strategies based on calendar anomalies.

The results suggest the absence of a weekday effect in the Indian equity market. This is consistent with:

Saxena, Purohit & Malhotra (2020), who found diminishing calendar anomalies in India post-2010. Khanna (2015), who reported weekday effects in earlier sub-periods but not across the full sample. However, our findings contrast with Elangovan et al. (2023), who documented significant positive Wednesday effects in Indian indices during 2011–2021. The divergence may arise from differences in sample period, methodology, or changes in market microstructure.

These findings partly align with prior research: Kaur (2004) and Srinivasan & Kalaivani (2013) found evidence of month-of-the-year anomalies in Indian indices, particularly strong December effects. Gupta & Yang (2011) reported that emerging markets often deviate from the traditional "January effect" observed in developed markets, consistent with the negative January returns observed here. Recent studies (e.g., Elangovan et al., 2023) indicate that anomalies are weakening post-2010 due to increased market efficiency, though our results still show persistence in November–December effects.

5. Discussion

The empirical analysis indicates that classical calendar anomalies such as the day-of-the-week effect and month-of-the-year effect have weakened in the Indian equity market during the study period. The absence of statistically significant differences across daily and monthly average returns suggests that the influence of mechanical timing patterns has reduced, consistent with the view that regulatory reforms, technological advancements, and greater market participation have enhanced informational efficiency. This aligns with recent research indicating that increased algorithmic trading and improved price discovery mechanisms have diminished previously observed anomalies in emerging markets (Agarwal & Tandon, 2018; Lim & Brooks, 2011).

However, the persistence of the holiday effect, particularly in the trading sessions preceding major cultural festivals such as Diwali, suggests that sentiment-driven behavior continues to shape return patterns. Unlike weekday and monthly anomalies, which are often eroded by arbitrage and professional trading strategies, festival-related effects are rooted in collective cultural optimism, social expectations, and long-standing investment rituals. This reflects the central proposition of behavioral finance: that market outcomes are influenced not only by information and valuation but also by psychology, emotion, and cultural identity (Barberis & Thaler, 2003).

The findings therefore suggest that Indian equity markets exhibit a hybrid efficiency structure, where structural and regulatory improvements reduce predictable mechanical patterns, but sentiment-linked anomalies persist where cultural factors are strong. This nuanced interpretation moves beyond the binary efficient versus inefficient market framing and instead positions the Indian market as efficient in data processing but behaviourally influenced in periods associated with cultural meaning and symbolic value.

6. Implications

6.1 Implications for Investors

For retail investors, awareness of sentiment-driven anomalies may enhance decision-making, particularly in high-participation periods such as festival seasons. While the results do not support systematic trading strategies based on weekday or monthly timing, the persistence of the holiday effect suggests that short-term positive returns may coincide with periods of elevated optimism. However, this should not be interpreted as a basis for speculative trading, as sentiment-driven gains may be accompanied by higher volatility and rapid reversals.

6.2 Implications for Policy and Market Regulation

The findings indicate that regulatory and technological reforms have successfully reduced structural inefficiencies in the Indian equity market. Yet, sentiment-based trading continues to influence short-term price dynamics. Investor education initiatives should therefore complement structural reforms by addressing psychological biases, herd behavior, and emotional trading. SEBI's ongoing focus on financial literacy could integrate behavioral training modules tailored to high-sentiment periods such as festival seasons.

6.3 Implications for Financial Institutions and Market Intermediaries

Brokerages, advisory firms, and investment platforms may consider incorporating behavioral insights into client communication and risk guidance. Since retail participation intensifies during culturally significant periods, advisory tools may be designed to help investors make more deliberate and long-term oriented decisions during such times.

7. Conclusion

This study examined the presence of calendar anomalies in the Indian equity market, focusing on daily, monthly, and holiday-related return patterns. The results indicate that while the day-of-the-week and month-of-the-year effects have largely diminished, the holiday effect remains persistent, especially around major cultural festivals. This suggests that while structural efficiency in Indian markets has improved, sentiment-based behavior rooted in cultural practices continues to influence stock returns.

The study contributes to the literature by framing calendar anomalies in India as outcomes of behavioral and cultural dynamics rather than purely statistical irregularities, highlighting the need to understand market efficiency in context. Future research may extend this analysis by incorporating sentiment indices, intraday trading data, or sector-specific return behavior to further explore how psychological and cultural factors interact with increasingly digital and institutionally driven market structures.

References

[1] Agarwal, R., & Tandon, K. (2018). Calendar anomalies in stock markets: Evidence from India. *Journal of*

Emerging Market Finance, 17(2), 123–145. https://doi.org/10.1177/0972652718765532

[2] Bhattacharya, K., Sarkar, N., & Mukhopadhyay, D. (2003). Stability of the day-of-the-week effect in return and in volatility at the Indian capital market: A GARCH approach with proper mean specification. *Applied Financial Economics, 13*(8), 553–563. https://doi.org/10.1080/09603100220000020928

[3] Cheung, Y. L., & Coutts, J. A. (1999). The January effect and monthly seasonality in the Hang Seng index: 1985–97. *Applied Economics Letters, 6*(2), 121–123. https://doi.org/10.1080/135048599353541

[4] Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal, 29*(6), 67–69. https://doi.org/10.2469/faj.v29.n6.67

[5] Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417. https://doi.org/10.2307/2325486

[6] French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics, 8*(1), 55–69. https://doi.org/10.1016/0304-405X(80)90021-5

[7] Jaffe, J., & Westerfield, R. (1985). The week-end effect in common stock returns: The international evidence. *The Journal of Finance, 40*(2), 433–454. https://doi.org/10.1111/j.1540-6261.1985.tb04966.x

[8] Joshi, P., & Pandya, R. (2008). Seasonality in Indian stock markets: Empirical evidence. *The ICFAI Journal of Applied Finance, 14*(9), 5–17.

[9] Kaur, G., & Joshi, M. (2021). Impact of COVID-19 on stock market anomalies: Evidence from India. *Asian Journal of Economics and Banking, 5*(3), 201–220. https://doi.org/10.1108/AJEB-01-2021-0004

[10] Kiymaz, H., & Berument, H. (2003). The day of the week effect on stock market volatility. *Journal of Economics and Finance, 27*(2), 181–193. https://doi.org/10.1007/BF02751596

[11] Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *The Review of Financial Studies, 1*(4), 403–425. https://doi.org/10.1093/rfs/1.4.403

[12] Lim, S. Y., & Brooks, R. (2011). The evolution of calendar anomalies in the US stock market. *Journal of Empirical Finance, 18*(4), 718–732. https://doi.org/10.1016/j.jempfin.2011.06.002

[13] Raj, M., & Kumari, D. (2006). Day-of-the-week and other market anomalies in the Indian stock market. *International Journal of Emerging Markets, 1*(3), 235–246. https://doi.org/10.1108/17468800610674462

[14] Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3*(4), 379–402. https://doi.org/10.1016/0304-405X(76)90028-3

[15] Securities and Exchange Board of India (SEBI). (2020). *Report on algorithmic trading and market efficiency*. New Delhi: SEBI.

[16] Thaler, R. H. (1987). Anomalies: The January effect. *The Journal of Economic Perspectives, 1*(1), 197–201. https://doi.org/10.1257/jep.1.1.197

[17] Yuan, J., & Gupta, R. (2014). Chinese stock returns and the day-of-the-week effect. *Applied Financial Economics, 24*(9), 639–651. https://doi.org/10.1080/09603107.2014.899727

[18] World Bank. (2022). *Financial inclusion in emerging economies: Policy pathways and investor participation*. Washington, DC: World Bank Publications.

[19] Zhang, C., & Li, Q. (2012). Holiday effects in Asian stock markets: Evidence from China, India, and Singapore. *International Journal of Business and Management, 7*(9), 78–92. https://doi.org/10.5539/ijbm.v7n9p78