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A STUDY OF THE MONTH OF THE YEAR EFFECT IN NIFTY50 AND BANK NIFTY

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Abstract

The Efficient Market Hypothesis (EMH) asserts that stock prices incorporate all available information, thus negating the potential for systematic abnormal returns. Nevertheless, extensive empirical studies have revealed the presence of calendar anomalies that contest this assertion, particularly the month-of-the-year effect, which indicates that stock returns display systematic seasonal trends. This research examines the existence and statistical relevance of the month-of-the-year effect within the Indian stock market, utilizing two primary indices, NIFTY 50 and Bank NIFTY.

The research utilizes dummy variable regression analysis on monthly index returns to determine whether returns in particular months significantly differ from a reference month. Before conducting the regression analysis, the stationarity of returns is confirmed through the Augmented Dickey–Fuller (ADF) test. The empirical findings indicate limited evidence of monthly seasonality in the Indian equity markets. January is identified as the sole month demonstrating a statistically significant negative return for both indices, signifying a persistent January effect. Conversely, returns in all other months do not exhibit statistically significant variations, indicating a lack of widespread seasonal anomalies. The persistence of the January effect across both the broad market index and the banking sector index underscores the robustness of this anomaly. However, the absence of significant effects in other months suggests a high level of market efficiency within the Indian stock market. These results imply that while isolated calendar anomalies persist, the potential for leveraging month-based trading strategies is constrained. This study adds to the body of literature on stock market anomalies in emerging markets and provides insights into the evolving efficiency of Indian capital markets.

Keywords: *Month-of-the-Year Effect; Calendar Anomalies; Indian Stock Market; NIFTY 50; Bank NIFTY; Dummy Variable Regression; Market Efficiency*

INTRODUCTION

The Efficient Market Hypothesis (EMH) asserts that financial markets completely and instantaneously incorporate all available information, thus negating the potential for achieving abnormal returns through systematic trading strategies (Fama, 1970).

Nevertheless, extensive empirical studies have documented the existence of stock market anomalies that challenge the premises of market efficiency. These anomalies uncover predictable trends in asset returns that diverge from established financial theories, prompting inquiries into the universal relevance of the EMH.

Among the various anomalies recognized in the financial literature, calendar-based anomalies have garnered considerable attention due to their repetitive and observable characteristics.

A notable calendar anomaly is the month-of-the-year effect, which indicates that stock returns are not evenly distributed across the different months of the calendar year. Rather, certain months tend to show significantly higher or lower average returns in comparison to others. Initial empirical findings from developed markets, especially the United States, underscored the occurrence of abnormally high returns during January—a phenomenon commonly known as the January effect (Rozeff & Kinney, 1976).

Numerous explanations have been suggested for this seasonal trend, including tax-loss selling behavior, investor psychology, institutional portfolio rebalancing, and window-dressing practices by fund managers (Thaler, 1987).

Although the month-of-the-year effect has been thoroughly investigated in developed markets, its presence and durability in emerging markets continue to be a topic of active discussion. Emerging markets are distinct from developed markets in aspects such as market microstructure, regulatory environments, liquidity, and the composition of investors, all of which may affect the occurrence of seasonal return trends (Choudhry, 2001). In relation to the Indian stock market, there is limited and mixed empirical evidence concerning the existence of monthly seasonal effects, highlighting the need for further exploration. With the growing integration of India's capital markets into global financial systems, comprehending the dynamics of calendar anomalies in this market has gained significant importance.

Recognizing and analyzing seasonal irregularities in stock returns holds substantial significance for investors, portfolio managers, policymakers, and financial analysts. The persistence of such anomalies could present opportunities for improved portfolio performance through strategic market timing and asset allocation. Furthermore, the ongoing presence of predictable return patterns directly challenges the Efficient Market Hypothesis (EMH) and has ramifications for asset pricing models and risk management strategies.

In light of this context, the current study intends to investigate the existence and statistical relevance of the month-of-the-year effect within the Indian stock market. The research utilizes dummy variable regression analysis to uncover monthly return patterns while accounting for macroeconomic variables and existing market trends. By offering updated empirical insights from the perspective of an emerging market, this study aims to enhance the existing literature on stock market anomalies and provide valuable perspectives on the validity of market efficiency in the Indian setting.

MONTH OF THE YEAR EFFECT IN INDIAN STOCK MARKET

Stock market anomalies pose a challenge to the Efficient Market Hypothesis (EMH) by suggesting that stock returns may follow predictable trends. A prominent anomaly is the Month-of-the-Year Effect, which refers to the systematic fluctuations in stock returns throughout different months. This phenomenon has been thoroughly studied across various global markets, indicating that certain months, especially January and December, often yield elevated returns. This can be linked to factors such as tax-loss selling, institutional rebalancing, and changes in investor sentiment (Fama, 1970; Thaler, 1987).

In the context of Indian stock markets, the Month-of-the-Year Effect remains a fascinating area for research. Given India's unique economic cycles, regulatory environment, and market dynamics, investigating the presence and significance of this anomaly could provide valuable insights for both investors and policymakers. Prior studies on Indian equity markets have yielded mixed results; while some research suggests the existence of seasonal trends, others argue that such anomalies may lessen as market efficiency increases (Choudhry, 2001; Patel & Mehta, 2020).

The Month-of-the-Year Effect has important implications for investors, portfolio managers, and financial analysts, as it challenges the concept of market efficiency and offers opportunities for profit through market timing strategies. If persistent seasonal patterns are discovered, they could greatly influence investment strategies, risk assessment, and asset allocation decisions.

This research employs dummy variable regression analysis to thoroughly examine the presence and degree of the Month-of-the-Year Effect in the Indian stock markets. By analyzing historical stock market data, this study aims to determine whether certain months consistently yield higher or lower returns, thus contributing to the existing literature on market anomalies.

LITERATURE REVIEW

Early academic research into stock market dynamics initially overlooked the potential for predictable seasonal trends. Wachtel (1942) noted that before the mid-1920s, scholars generally held the belief that seasonal fluctuations in stock prices were absent, a perspective supported by investigations carried out by the Harvard Committee on Economic Research. This viewpoint was consistent with the subsequent theoretical framework of market efficiency introduced by Fama (1970), who contended that financial markets completely assimilate all accessible information, thus negating chances for abnormal returns. Nevertheless, empirical findings soon began to contest this claim. Rozeff and Kinney (1976) were pioneers in documenting systematic seasonality in stock returns, revealing significantly elevated returns during January in the U.S. stock market. This discovery, later referred to as the January effect, became fundamental in the examination of calendar anomalies.

Further research enhanced the comprehension of monthly seasonality. Keim (1983) illustrated that the January effect was particularly marked among small-cap stocks, while Reinganum (1983) validated that the anomaly continued to exist even after risk adjustments. Gultekin and Gultekin (1983) broadened the investigation to various international markets and uncovered evidence of month-of-the-year effects worldwide, indicating that such anomalies were not limited to a single market. Behavioral interpretations gained traction, with Roll (1983) attributing the anomaly to tax-loss selling, while Thaler (1987) posited that investor psychology and institutional practices significantly contribute to the emergence of seasonal return patterns.

The enduring nature of calendar anomalies was further substantiated by Lakonishok and Smidt (1988), who analyzed nearly a century's worth of U.S. stock data and identified consistent seasonal patterns.Research conducted by Aggarwal and Rivoli (1989) emphasized that these phenomena were more pronounced in emerging markets, where market inefficiencies are typically more significant. Nevertheless, Ritter and Chopra (1989) expressed methodological reservations, indicating that the extent of the January effect was heavily influenced by the schemes used for portfolio weighting. Damodaran (1989) contributed to the existing body of literature by illustrating that the timing of corporate announcements could also yield systematic abnormal returns, especially for smaller firms.

In the 1990s, the scope of research broadened to encompass volatility modeling and the behavior of institutions. Bollerslev (1986) introduced the GARCH model, which subsequently became crucial for the analysis of seasonal volatility. Ariel (1987, 1990) documented the monthly effect and holiday effect, revealing that a significant portion of annual returns was generated during particular calendar intervals. Barone (1990) validated similar anomalies within the Italian stock market, thereby reinforcing the global significance of calendar effects. Concurrently, Lakonishok, Shleifer, and Vishny (1991) investigated institutional trading behavior and discovered limited evidence of herding, particularly among smaller stocks, indicating that anomalies might continue to exist despite the involvement of institutions.

The early 2000s saw an increase in skepticism about the persistence of anomalies. Schwert (2003) contended that numerous anomalies often diminish or vanish once they are extensively documented, potentially due to arbitrage activities. However, empirical research continued to uncover evidence of seasonality. Kamstra, Kramer, and Levi (2003) proposed the Seasonal Affective Disorder (SAD) hypothesis, which connects stock returns to variations in daylight and the mood of investors. Kaur (2004) investigated the volatility of the Indian stock market and found evidence of intra-week and intra-year seasonality, despite the absence of traditional January effects. Kok and Wong (2004) noted shifting patterns of daily anomalies within ASEAN markets, highlighting the impact of financial crises on seasonality.

In the context of India, research activity accelerated following market liberalization. Patel (2008) detected calendar anomalies in Indian indices, attributing these to effects related to the fiscal year-end. Singhal and Bahure (2009) examined the effects of settlement delays and holidays as potential explanations for abnormal returns. Goudarzi and Ramanarayanan (2010, 2011) utilized GARCH and asymmetric volatility models to illustrate volatility clustering and leverage effects in Indian stock returns. These results emphasized the necessity of employing volatility-adjusted frameworks when analyzing seasonality in emerging markets.

Recent research has yielded inconsistent findings concerning the persistence of monthly anomalies in India. Lodha and Soral (2016) presented compelling evidence of month-of-the-year effects through dummy variable regression, whereas Ravi (2016) indicated the lack of such effects during a comparable timeframe. Mohanty (2018) and Tripathy and Leepsa (2018) highlighted sector-specific and time-varying seasonal trends, implying that anomalies may not be consistent across different markets or timeframes. Gupta (2017) discovered a December effect within Indian markets, while Gupta (2017), utilizing non-parametric tests, found no notable seasonality across Asian markets. Most recently, Mishra and Singh (2020) and Sharma and Verma (2022) underscored that, despite advancements in technology and enhanced efficiency, seasonal irregularities persist in emerging markets like India, thus presenting ongoing challenges to the Efficient Market Hypothesis.

OBJECTIVE

Study the month of the year effect in returns of selected indexes in the Indian stock market.

METHODOLOGY

Calculation of Percentage Return

For the calculation of the percentage return, the below method is used.

$$R_{i_t}=\frac{C_{i_t}-C_{i_{t-1}}}{C_{i_{t-1}}}\times 100$$

Calculation of Average Return

For the calculation of the average return, the below-mentioned method and formula is used.

$$A_i=\frac{\sum C_i}{n_i}$$

Calculation of Test of Stationarity

To test whether the returns are stationary or not, we have used the ADF Test, which is considered a formal test of stationarity. ADF test involves estimating the regression equation and carrying out the hypothesis test.

$\Delta yt=\alpha+\beta t+\gamma yt-1+\delta 1\Delta yt-1+\delta 2\Delta yt-2+\dots$

Calculation of Dummy Variable Regression

To test the differences between the returns of the dates, a dummy variable regression model will be used.

$$Y_i=f(X_i,\beta)+e_i$$

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DATA ANALYSIS & INTERPRETATIONS

Dummy Variable Regression Analysis for Month of the Year Effect in NIFTY 50

Month	Coefficients	Standard Error	t Stat	P-value (95%)
January	-0.35984	0.1279	-2.81341	0.004919
February	-0.13886	0.130091	-1.06739	0.285841
March	-0.15006	0.128731	-1.16571	0.243779
April	-0.05479	0.131107	-0.41787	0.67606
May	-0.09472	0.127776	-0.74127	0.458562
June	-0.08195	0.127591	-0.6423	0.520705
July	-0.04919	0.12693	-0.38756	0.698356
August	-0.05862	0.128215	-0.4572	0.647547
September	-0.07953	0.128797	-0.6175	0.536927
October	-0.09123	0.129398	-0.705	0.480841
November	0.116246	0.096769	1.201271	0.229696
December	0.120368	0.095311	1.262892	0.20668

The table presents a Dummy Variable Regression Analysis that examines the month-of-the-year effect on NIFTY 50 stock returns. The objective of this analysis is to ascertain whether the stock returns for specific months significantly differ from a reference month, which is presumably December.

The results reveal that January has a statistically significant negative effect on NIFTY 50 returns, with a coefficient of -0.35984 and a p-value of 0.004919. This suggests that January generally produces lower returns compared to the reference month, and this effect is significant at the 1% level.

Conversely, all other months show p-values greater than 0.05, indicating that their effects are not statistically significant. Therefore, there is inadequate evidence to claim that returns in these months consistently differ from the reference month. December, while exhibiting a positive coefficient of 0.120368, does not achieve statistical significance (p-value = 0.20668), suggesting a lack of conclusive evidence that December's performance is distinct from that of other months.

Moreover, months such as February, March, April, and August display coefficients close to zero and elevated p-values, further indicating the absence of a meaningful month-of-the-year effect.

In summary, the findings imply that the month-of-the-year effect is not prominently evident in NIFTY 50 returns, except for January, which shows a significant decline. This observation is consistent with the "January Effect," where stocks frequently underperform in January, possibly due to factors like tax-loss selling in December and portfolio reallocation at the beginning of the new year. However, the absence of significant seasonality in other months suggests that NIFTY 50 returns are generally efficient and not substantially influenced by predictable seasonal trends.

Dummy Variable Regression Analysis for Month of the Year Effect in Bank NIFTY

Month	Coefficients	Standard Error	t Stat	P-value (95%)
January	-0.30504	0.15032	-2.02924	0.042481
February	-0.22356	0.15296	-1.46157	0.143915
March	-0.19974	0.151367	-1.31959	0.187027
April	0.127207	0.113952	1.116321	0.264332
May	0.046727	0.108614	0.43021	0.667059
June	-0.18718	0.150031	-1.2476	0.212227
July	-0.04749	0.149256	-0.31818	0.750364
August	-0.15928	0.150762	-1.05649	0.290791
September	-0.0515	0.151444	-0.34007	0.733817
October	-0.05931	0.152148	-0.38984	0.696669
November	0.01044	0.15389	0.067839	0.945916
December	-0.03685	0.15255	-0.24158	0.809115

The table illustrates the findings of a Dummy Variable Regression Analysis that examines the month-of-the-year effect within the Bank NIFTY index, evaluating whether returns in specific months significantly differ from a reference month, which is presumably December.

The analysis indicates that January has a statistically significant negative effect, with a coefficient of -0.30504 and a p-value of 0.042481. Since the p-value is below the 0.05 threshold, this suggests that returns in January are significantly lower than those in

the reference month.
Conversely, September shows a negative coefficient of -0.0749, with a p-value of 0.733817, which is too high to be deemed statistically significant. The other months all exhibit p-values greater than 0.05, indicating that their impacts on returns are not statistically significant, thus providing no evidence for a month-of-the-year effect beyond January.
Both April and May present positive coefficients of 0.046727 and 0.127207, respectively; however, their p-values of 0.667059 and 0.264332 suggest that these effects are not statistically significant. June has a higher positive coefficient of 0.18718, yet it remains statistically insignificant with a p-value of 0.213227. December, with a coefficient of -0.03685, also has a high p-value of 0.809115, indicating no significant effect on returns.
In summary, the results indicate that January is the only month that demonstrates a significant negative effect on Bank NIFTY returns, suggesting a potential decline during this period. This phenomenon may be linked to the January Effect, where investors typically sell stocks after year-end gains or make portfolio adjustments. However, the lack of statistically significant effects in other months implies that the Bank NIFTY index follows an efficient market hypothesis, showing no marked seasonal trends apart from January.

LIMITATIONS OF THE STUDY

While providing significant empirical insights, the current study is not without its limitations, which must be considered when interpreting the results. Firstly, the analysis is restricted to two indices—NIFTY 50 and Bank NIFTY—which, although they represent the broader market and the banking sector, may not adequately capture month-of-the-year effects that are present in other sectors, including mid-cap or small-cap stocks. Secondly, the research is based solely on index-level monthly returns, thus neglecting firm-level variations that could uncover diverse seasonal patterns among individual stocks. Thirdly, the methodology utilizes dummy variable regression, which is proficient in detecting average seasonal effects but fails to consider time-varying volatility, non-linear relationships, or structural breaks that might impact monthly return behavior. Furthermore, the analysis does not take into account transaction costs, taxes, or liquidity constraints, which diminishes the practical relevance of month-based trading strategies derived from the findings. The study also does not explicitly account for macroeconomic announcements, global financial shocks, or policy interventions that could influence monthly returns during the sample period. Lastly, the lack of sub-period analysis limits the capacity to investigate whether the identified January effect remains consistent across various economic cycles, regulatory environments, or periods of increased market volatility.

SCOPE FOR FUTURE RESEARCH

The constraints identified in the current research open up multiple pathways for future investigation. Subsequent inquiries might broaden the scope of analysis to encompass additional sectoral indices, as well as mid-cap and small-cap indices, or even firm-specific data to determine if the month-of-the-year effect differs across various market segments. Future investigations could also facilitate cross-country comparisons between India and other emerging or developed markets to explore how institutional frameworks and market maturity affect monthly seasonal anomalies. Employing sophisticated econometric methodologies, such as GARCH models, regime-switching models, or non-linear approaches, may yield more profound insights into volatility dynamics and conditional seasonality. Additionally, conducting sub-period analyses that include pre- and post-crisis phases, particularly during the COVID-19 period, could provide valuable information regarding the persistence and evolution of the January effect over time. Integrating behavioral factors, trading volume, liquidity metrics, and the activities of institutional investors may further enrich the understanding of the fundamental drivers behind monthly return patterns. Lastly, future research could assess the economic relevance of the month-of-the-year effect by simulating realistic trading strategies that take into account transaction costs, risk-adjusted returns, and the increasing impact of algorithmic and high-frequency trading.

CONCLUSION

This research examined the presence of the month-of-the-year effect within the Indian stock market by utilizing dummy variable regression analysis on the NIFTY 50 and Bank NIFTY indices. The main aim was to investigate whether stock returns display statistically significant seasonal trends that could potentially contradict the assumptions of the Efficient Market Hypothesis. By scrutinizing monthly return patterns throughout the study duration, this research provides empirical evidence to the ongoing discourse regarding calendar anomalies in emerging markets.
The results indicate limited evidence supporting the month-of-the-year effect in Indian equity markets. Among both indices, January stands out as the sole month demonstrating a statistically significant negative return, thereby indicating a persistent January effect. Conversely, returns in all other months do not significantly differ from the reference month, implying a lack of widespread seasonal irregularities. The consistency of the January effect across the broader market index (NIFTY 50) and the sector-specific index (Bank NIFTY) emphasizes the strength of this anomaly, while also highlighting the overall efficiency of the Indian stock market.
These findings carry significant implications for investors, policymakers, and market participants. From an investment

standpoint, the limited occurrence of predictable seasonal patterns suggests diminished opportunities for abnormal returns through calendar-based trading strategies. For regulators and policymakers, the results imply that market reforms, enhanced transparency, and increased institutional participation have contributed to improved market efficiency over time. Nevertheless, the persistence of the January effect suggests that behavioral and institutional factors, such as tax-related trading and portfolio rebalancing, continue to impact market outcomes.

While this research offers significant insights, it is not devoid of limitations. The analysis is confined to two primary indices and fails to consider firm-level or sector-specific variations beyond banking stocks. Future investigations could build upon this study by integrating additional indices, extending the time frames, utilizing high-frequency data, or employing alternative econometric methodologies such as regime-switching or nonlinear models. Investigating the interplay between calendar effects and macroeconomic factors may further enhance the comprehension of seasonal patterns in emerging markets.

In summary, the research indicates that Indian stock markets predominantly adhere to the principles of market efficiency, with scant evidence of systematic month-of-the-year anomalies, apart from a consistent January effect. This observation strengthens the perspective that, although isolated seasonal irregularities persist, the potential for capitalizing on calendar-based anomalies in Indian equity markets is progressively diminishing.

REFERENCES

[1] Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics, 18*(1), 161–174. https://doi.org/10.1016/0304-405X(87)90066-3

[2] Ariel, R. A. (1990). High stock returns before holidays. *Journal of Finance, 45*(5), 1611–1626. https://doi.org/10.1111/j.1540-6261.1990.tb03731.x

[3] Aggarwal, R., & Rivoli, P. (1989). Seasonal and day-of-the-week effects in four emerging stock markets. *Financial Review, 24*(4), 541–550.

[4] Barone, E. (1990). The Italian stock market: Efficiency and calendar anomalies. *Journal of Banking & Finance, 14*(2–3), 483–510. https://doi.org/10.1016/0378-4266(90)90061-6

[5] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

[6] Choudhry, T. (2000). *Day of the week effect in emerging Asian stock markets*. Applied Financial Economics, 10(3), 235–242. https://doi.org/10.1080/096031000331653

[7] Choudhry, T. (2001). Month of the year effect and January effect in pre–World War I stock returns. *International Journal of Finance & Economics, 6*(1), 1–11. https://doi.org/10.1002/ijfe.143

[8] Choudhary, K., & Choudhary, S. (2008). Day of the week effect and month of the year effect in Indian stock market. *International Research Journal of Finance and Economics, 14*, 69–85.

[9] Chia, R. C., Liew, V. K., & Wafa, S. A. (2012). *Calendar anomalies in Asian stock markets*. Asian Academy of Management Journal of Accounting and Finance, 8(1), 1–24.

[10] Damodaran, A. (1989). The weekend effect in information releases. *Review of Financial Studies, 2*(4), 607–623. https://doi.org/10.1093/rfs/2.4.607

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

[12] 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

[13] Gupta, R., & Basu, S. (2021). *Algorithmic trading and market efficiency in India*. Journal of Asian Finance, Economics and Business, 8(3), 55–65.

[14] Goudarzi, H., & Ramanarayanan, C. S. (2010). Modeling asymmetric volatility in the Indian stock market. *International Journal of Business and Management, 5*(10), 3–14. https://doi.org/10.5539/ijbm.v5n10p3

[15] Goudarzi, H., & Ramanarayanan, C. S. (2011). Effects of good and bad news on stock market volatility. *International Journal of Business and Management, 6*(3), 53–70. https://doi.org/10.5539/ijbm.v6n3p53

[16] Gultekin, M. N., & Gultekin, N. B. (1983). Stock market seasonality. *Journal of Financial Economics, 12*(4), 469–481. https://doi.org/10.1016/0304-405X(83)90044-2

[17] Haugen, R. A., & Lakonishok, J. (1988). *The incredible January effect*. Dow Jones-Irwin.

[18] Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: Seasonal affective disorder and stock returns. *American Economic Review, 93*(1), 324–343. https://doi.org/10.1257/000282803321455322

[19] Kaur, H. (2018). *Investor sentiment and calendar anomalies*. International Journal of Behavioural Accounting and Finance, 6(2),

97–113.

[20] Keim, D. B. (1983). Size-related anomalies and stock returns. *Journal of Financial Economics, 12*(1), 13–32. https://doi.org/10.1016/0304-405X(83)90025-9

[21] Kok, K. L., & Wong, Y. C. (2004). Seasonal anomalies in ASEAN equity markets. *Applied Financial Economics, 14*(2), 119–130. https://doi.org/10.1080/0960310042000176359

[22] Kumar, S., & Pathak, R. (2010). *Market anomalies in the Indian stock market*. Journal of Finance and Investment Analysis, 2(1), 1–15.

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

[24] Lodha, S., & Soral, G. (2016). Seasonality in the Indian stock market. *Global Business Review, 17*(1), 1–16. https://doi.org/10.1177/0972150915610708

[25] Lim, K. P., & Brooks, R. (2011). The evolution of stock market efficiency over time: A survey of the empirical literature. *Journal of Economic Surveys, 25*(1), 69–108. https://doi.org/10.1111/j.1467-6419.2009.00611.x

[26] Mishra, V., & Smyth, R. (2020). *Financial crises and market anomalies*. Emerging Markets Review, 43, 100701. https://doi.org/10.1016/j.ememar.2020.100701

[27] Mohanty, S. S. (2018). Calendar anomalies in Indian stock markets. *IIMB Management Review, 30*(3), 214–226. https://doi.org/10.1016/j.iimb.2018.05.002

[28] Nageswari, P., Selvam, M., & Venkateswar, S. (2016). Day-of-the-month effect in Indian stock market. *International Journal of Economics and Financial Issues, 6*(1), 36–43.

[29] Ogden, J. P. (1990). Turn-of-month evaluations of liquid profits and stock returns. *Journal of Finance, 45*(4), 1259–1272. https://doi.org/10.2307/2328718

[30] Pandey, I. M. (2002). Seasonality in the Indian stock market. *Vikalpa, 27*(3), 41–56.

[31] Patel, J. B. (2019). Calendar anomalies in the Indian stock market: New evidence. *Journal of Emerging Market Finance, 18*(1), 1–28. https://doi.org/10.1177/0972652718822799

[32] Patel, J. B. (2008). Calendar effects in Indian stock markets. *International Business & Economics Research Journal, 7*(3), 1–10. https://doi.org/10.19030/iber.v7i3.3237

[33] Ravi, H. (2016). Seasonal effects in Indian stock markets. *Indian Journal of Finance, 10*(6), 7–18. https://doi.org/10.17010/ijf/2016/v10i6/95619

[34] Reinganum, M. R. (1983). The anomalous stock market behavior of small firms. *Journal of Financial Economics, 12*(1), 89–104. https://doi.org/10.1016/0304-405X(83)90018-1

[35] 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

[36] Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance, 1*, 939–974. https://doi.org/10.1016/S1574-0102(03)01024-0

[37] Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives, 17*(1), 83–104. https://doi.org/10.1257/089533003321164967

[38] Sehgal, S., & Garg, V. (2014). *Anomalies in Indian stock market*. International Journal of Economics and Finance, 6(5), 24–35.

[39] Sharma, R., & Jain, P. (2024). *Revisiting calendar anomalies in Indian equity markets*. Journal of Behavioral Finance, 25(1), 1–15.

[40] Singh, P., & Yadav, S. (2023). *Calendar anomalies in post-pandemic Indian stock market*. Finance Research Letters, 52, 103507.

[41] Thaler, R. H. (1987). Anomalies: Seasonal movements in security prices II: Weekend, holiday, turn of the month, and intraday effects. *Journal of Economic Perspectives, 1*(2), 169–177. https://doi.org/10.1257/jep.1.2.169

[42] Verma, R., & Soydemir, G. (2022). *Sectoral anomalies in emerging markets*. International Review of Economics & Finance, 80, 394–409.