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# Impact of Month of the Year Anomaly on Indian Stock Market: A Sectoral Analysis

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**Abstract:**
Stock market anomalies refer to instances where certain securities or groups of securities deviate from the efficient market hypothesis, which posits that security prices should always reflect all available information and incorporate new information rapidly. Seasonal variations in the stock market are a well-established phenomenon in different sectors of the economy. Within a time frame of less than one year, time series data often display periodic fluctuations characterized by regular and repetitive seasonal patterns. Consequently, stock returns may reveal systematic patterns at specific times of the day, week, or month. This paper explores the month-of-the-year effect across the financial services sector of the economy by analyzing monthly performance patterns and determining whether any particular month exhibits performance levels that significantly surpass those of other months. The sector indices of Nifty Financial Services from 2016 to 2024 have been used to achieve the objective of this study. The findings of this study will provide investors with insights to develop strategies that capitalize on these temporal variations, potentially enhancing returns during specific months.

**Keywords**: Month of the Year effect, Market Anomalies, Seasonal Variations, Nifty, Financial Services Sector

## INTRODUCTION

In general, the term ‘anomaly’ refers to a situation that differs from the norm. In Finance, calendar anomalies describe a return pattern that repeats itself at a certain time. These are also called seasonal effects, which are "the trend of financial assets returns to display systematic patterns in a given time of day, week, month or year" (Brooks, 2008). Anomalies in the stock market refer to the imperfections in how market participants evaluate and incorporate available information. In the present study, the market anomalies present in the form of the seasonality effect are examined. Seasonality effect can be understood as the impact of a month of a year on the stock price behaviour. The seasonal effect implies that all the months in a year do not have a similar effect on stock price movement. Some of the months in a year have more effect on the stock price movement than other months in the same year. This calendar effect is associated with momentous discrepancies in the means of returns of disparate intervals between dates in consecutive months, i.e. significantly dissimilar (high or low) returns are generated in a particular month than in the rest of the year.

## REVIEW OF LITERATURE

**Camilleri, S. J. (2008)** investigated in their study whether the Malta Stock Exchange exhibits monthly volatility patterns akin to other stock markets using various statistical techniques. It examines the Turn-of-the-Month and January effects, noting that increased volatility is often associated with company announcement timings and other factors identified in prior research.

**Borges, M. R. (2009)** studied the impact of day-of-the-week and month-of-the-year effects on seventeen European stock market indexes from 1994 to 2007. By using robust techniques like GARCH modeling and bootstrapping, the study found insufficient evidence for significant calendar effects, despite some lower returns in August and September. Country-specific effects varied and were not consistently present, undermining the belief that calendar anomalies are merely data mining artifacts.

**Li, B., & Liu, B. (2010)** in their study of New Zealand's stock market found significant monthly return patterns. In June, four industry indices had positive returns, while August saw negative performance in three market indices and eight industry indices, potentially due to severe weather. The January effect was absent in market indices, and only two industry indices showed it. No significant seasonal irregularities were observed, challenging the notion of tax-loss selling affecting returns.

**Verma, A., & Kumar, C. V. R. S. V. (2012)** in their study on the Bombay stock market analyzed 20 years of monthly returns for the BSE Sensex to assess the month of the year effect. The study found no significant variance in returns across months using OLS regression and the Kruskal-Wallis test. Specifically, no notable differences were observed in January or April returns, indicating that the month of the year has no substantial impact on market performance. Overall, the data indicates that there is no significant influence of the month of the year on the Bombay stock market.

**Neeraja, P., & Srikanth, P. (2014)** reviewed the evolution of efficient market theory, highlighting Fama's 1970 Efficient Market Hypothesis with its weak, semi-strong, and strong forms. They study revealed that while the semi-strong form has practical implications, the weak and strong forms are less applicable. Their study examines seasonal anomalies in the Indian stock market using BSE-Sensex and BSEIT Index data from April 1999 to March 2013, finding that BSE-Sensex significantly affects IT sector volatility.

**Jassal, T., & Dhiman, B. (2015)** analyzed in their study the Month of the Year effect on BSE Sensex, Small Cap, and Mid-Cap equities from 2006 to 2013 using the GARCH (1, 1) model. It identifies significant September effects across all indices, notable April effects only in Mid-Cap and Small Cap, and a negative February effect in Mid-Cap and Small Cap. BSE Sensex shows no abnormality for April or February. The findings suggest opportunities for anomalous returns, indicating market inefficiency.

**Kumar, H., & Dawar, M. (2017)** The study examines seasonal patterns in Indian stock markets by analyzing calendar effects on BSE Sensex, BSE 200, and BSE 500 indices from 1999 to 2015. Findings reveal significant seasonality in BSE 200 and BSE 500 but not in Sensex, indicating a lack of informational efficiency in the Indian stock market. The seasonality is shown in both the month-of-the-year and days-of-week effects. It indicates that Indian stock markets lack informational efficiency, even in its weak version. The study concludes that by using the detected irregularities in the returns of the Indian stock market, the discovered patterns can be useful in determining the timing of transactions.

**Arendas, P., & Kotlebova, J. (2019)** analyzed the Turn of the Month Effect across stock markets in eleven Central and Eastern European countries from 1999 to 2018. They found that seven countries exhibited significantly higher returns during the transition between months. However, this effect does not influence price volatility; it primarily impacts stock market returns. Their study highlights the presence of this calendar anomaly in the region's markets.

## OBJECTIVES OF THE STUDY

The main objective of the present study is to examine the anomaly of Month-of-the-year effect on Indian financial services sector stocks.

## HYPOTHESIS OF THE STUDY

To meet the objective of the present study, the following hypothesis is formulated:
**H0** (**Null Hypothesis)**: There is no Month-of-the-year effect on the stocks of companies under Indian financial services sector.
**H1 (Alternative Hypothesis)**: Month-of-the-year effect on the stocks of companies under Indian financial services sector is present.

## RESEARCH METHODOLOGY

Keeping in view the objectives of the study, closing stock prices from the selected index of National Stock Exchange 500 of the financial service sector listed in NSE was collected using Prowess Software from January 1, 2015 to April 15, 2024. For the proposed study, all companies within the financial services sector that were listed on the NSE during this timeframe were considered and to GARCH Test was adopted to model and analyze time-varying volatility in financial time series data.

## DATA ANALYSIS AND INTERPRETATION

**Table 1:** Month-of-the-year effect on the stocks of companies in the Indian financial services sector

| Month-of-the-year effect in the Indian financial services sector | | | | |
|---|---|---|---|---|
| **Coefficients** | **Estimate** | **Std. Error** | **t-value** | **Pr(>\|t\|)** |
| **January** | **-0.038** | **0.125** | **-0.301** | **0.764** |
| **February** | **-0.002** | **0.160** | **-0.011** | **0.992** |
| **March** | **0.220** | **0.152** | **1.440** | **0.150** |
| **April** | **0.183** | **0.139** | **1.319** | **0.187** |
| **May** | **0.227** | **0.140** | **1.621** | **0.105** |
| **June** | **0.041** | **0.133** | **0.311** | **0.756** |
| **July** | **0.228** | **0.146** | **1.568** | **0.117** |
| **August** | **0.097** | **0.145** | **0.667** | **0.505** |
| **September** | **0.003** | **0.153** | **0.017** | **0.986** |
| **October** | **0.160** | **0.144** | **1.109** | **0.267** |
| **November** | **0.164** | **0.142** | **1.152** | **0.249** |
| **December** | **0.087** | **0.137** | **0.633** | **0.527** |
| **Omega** | **0.033** | **0.010** | **3.272** | **0.001** |
| **alpha 1** | **0.090** | **0.022** | **4.001** | **0.000** |
| **beta 1** | **0.891** | **0.021** | **41.799** | **0.000** |
| **Log Likelihood** | **-3531.011** | | | |
| **Akaike Information Criteria** | **3.109** | | | |
| **Residuals Diagnostics** | **Statistic** | | **p-value** | |
| **Ljung-Box Q-Test** | **10.790** | | **0.001** | |
| **Ljung-Box Q-Square** | **0.115** | | **0.735** | |
| **Arch-LM Test** | **1.023** | | **0.312** | |

Notes:- *,**,*** represent significant p-values at 10%,5% and 1% levels, respectively.

The above Table presents the month effect on the Nifty Financial Services (FS) sector index in India, examining the potential calendar anomalies across different months. The estimates reflect the monthly coefficients, while the associated standard errors, t-values, and p-values assess their statistical significance. For each month, the estimates are: January (-0.038), February (-0.002), March (0.220), April (0.183), May (0.227), June (0.041), July (0.228), August (0.097), September (0.003), October (0.160), November (0.164), and December (0.087). The t-values and p-values indicate the statistical significance of these estimates. None of the monthly effects show statistically significant p-values at the conventional levels (10%, 5%, or 1%), suggesting that there are no significant monthly anomalies in the Nifty Financial Services Index. The table also includes parameters for the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, with omega (0.348), alpha1 (0.090), and beta1 (0.891). Both alpha1 and beta1 parameters are statistically significant, as indicated by their p-values (0.000 and 0.000, respectively), suggesting a strong GARCH effect where past volatility influences current volatility. Omega, however, is not statistically significant with a p-value of 0.001. Model diagnostics include the log likelihood (-3531.011) and the Akaike Information Criterion (3.109), which are used for model comparison and selection. The residual diagnostics, including the Ljung-Box Q-Test, Ljung-Box Q-Square, and ARCH-LM Test, show high p values (0.231, 0.735, and 0.312, respectively), indicating that the residuals do not exhibit significant autocorrelation or ARCH effects, confirming the adequacy of the GARCH model.

## CONCLUSION

Seasonality studies are among the most rigorously examined phenomena in the stock market. Investors frequently seek to determine if specific temporal events offer opportunities to achieve abnormal returns and outperform the market. This study aims to analyze the effect of the month-of-the-year event on investment returns within the financial services sector of the Indian stock market.

The research findings indicate that there are no significant monthly anomalies affecting the Nifty Financial Services Index. The results do not support the presence of seasonality within the Indian stock market. However, the significant GARCH parameters suggest that volatility is persistent and influenced by past shocks, with model diagnostics confirming the fit and validity of the model. Consequently, it can be concluded that investors cannot leverage seasonal effects to achieve abnormal returns. Overall, the study does not support the existence of seasonal effect in the market.

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