Calendar Anomalies in The Indian Stock Market - An Emperical Study

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Abstract

Stock market anomalies are based on the premise that if the stock market is efficient and follows a random walk, the stock prices will reflect all available information at any point in time resulting in a zero probability of superior market returns. This aspect would lead to a zero probability to predict changes in the stock prices based on past price behaviour. Innumerable research studies have been undertaken across the globe to find the existence of an efficient market. The studies have inferred that there exists certain anomalies and have also offered explanations for such occurrence. This study is motivated to comprehend and identify whether calendar anomalies exist in the Indian stock market and if the results are affirmative, whether it would be possible for investors to benefit from such anomalies especially given the understanding that India is designated to be the best destination for investment purposes due to a growing economy owing to several macro-economic factors. Based on this, this study will conclude the consequences to help prospective investors make their investment decisions accordingly. The paper examined the Nifty 50 Index to observe whether there exist calendar anomalies. The study spans the period from January 1997 to December 2016 and attempts to evaluate the 'day-of-the-week effect', 'turn-of-the-month effect', 'month-of-the-year effect' and 'January effect'.

The results of this study showed that 'day-of-the-week' effect was prevalent in Nifty 50. It was observed that Nifty 50 demonstrated the 'turn-of-the-month' effect to a large extent, which emphasised the fact that investors have the potential to create superior returns in the 'turn-of-the-month' days. 'Month-of-the-year' effect and 'January effect' was not observed in Nifty 50.

The results of this study established that there are patterns in the Indian stock market, which may be applied to get superior returns, confirming that the-Efficient Market Hypothesis (EMH) is not established in the Indian market. The study also signifies that there exists anomalies and investors can improve their returns by timing their investments according to these anomalies.

This paper is distinctive as it has examined the largest duration in the Indian context to observe the anomalies existing in the Indian market. The long time series is undertaken to safeguard against the sample selection bias, data snooping and noise as the small sample period inference could potentially bias the inferences of the empirical findings. It is empirical in nature and the application of econometric technique makes the result more reliable. This paper is a guide for Foreign Institutional Investors (FIIs), portfolio managers and retail investors to carry out their investment strategies.

Key Words: *EMH, Calendar Anomalies*

Introduction

Financial anomalies refer to situations where the empirical results seem to be inconsistent with the Efficient Market Hypothesis (EMH). Studies across the world have suggested that equity markets contradict the established theories like Efficient Market Hypothesis (EMH), which are difficult to explain through common rationale. Eugene Fama emphasised the fact that anomalies are either quickly priced out of the market or may be explained through the market microstructure arguments. He emphasised that cognitive biases are distinct from social biases. The former can be averaged out by the market while the latter can create positive feedback loops that drive the market further away from fair price equilibrium. Research confirms that stock exchanges across the world often witness deviations from the rules of EMH, which is referred to as anomalies. These anomalies are indicators of specific trading strategies in the market and thereby give an opportunity to earn super normal profits. Studies have documented the reasons for such anomalies, which are primarily attributed to the timing, response by investors to information, strategic policy decisions and macroeconomic events, which results in higher profits. According to Zeimba and Hensel (1994), if an investor is able to take advantage of such anomalies, superior returns can be earned.

This paper primarily makes an attempt to investigate four major calendar anomalies namely: 'Day-of-the-week effect', 'turn-of-the-month effect', 'month-of-the-year effect' and 'January effect'.

Review of Literature

According to Habbard (2008), anomalies are trading opportunities that arise from stock trading strategies, which can result in super normal returns. Fama and French (2008) explained that there are patterns in average stock returns that are considered anomalies as they are not explained by traditional asset pricing models like the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). While the paper dealt mostly with fundamental anomalies, it gave an excellent glimpse of how pervasive these anomalies are.

EMH reinforces that markets are rational and the asset prices fully reflect all the information primarily due to the technological advancement leading to real time information dissemination to investors in a homogeneous manner, which leads to zero probability of generating abnormal returns. Eugene Fama supported that anomalies are either quickly priced out of the market or explained by appealing market microstructure arguments. He argued that individual cognitive biases are distinct from social biases. The former can be averaged out by the market, while the latter can create positive feedback loops that drive the market further away from fair price equilibrium. Similarly, for an anomaly to violate market efficiency, an investor must be able to trade against it and earn an abnormal profit.

Studies of anomalies are challenging and provide interesting inputs for portfolio management. Several studies have pointed out the reasons for such anomalies to be due to timing, response by investors to information, strategic policy decisions, macroeconomic events, etc. Due to such events, the actual returns differ widely from what is generally expected.

Calendar Anomalies

It refers to the existence of any irregularities, fluctuations or the specific pattern occurring in a recurring manner during a definite time within a year. Calendar anomalies may include different effects such as weekend effect, day-of-the-week effect, turn-of-the-month effect, time-of-the-day effect, and month-of-the-year effect.

Day-of-the-week effect

This anomaly states that on some of the days of the week, stock prices tend to move more than on other days, and that there exists bias towards positive market performance on specific days. Although the difference between the returns may not be huge, the patterns are observed to be consistent and recurring in nature. Some of the studies have found that Mondays typically give lower returns versus Fridays and there could be psychological reasons, among other factors, for such returns. On Friday, the end of the week, financial markets witness higher optimism and investors look forward to the weekend, which results in better-than-average trading activity. On the other side, investors tend to analyse, think over their investment preference over the weekend and thus when they are back on Monday, they tend to be more cautious.

The phenomenon of day-of-the-week effects has been extensively researched over the last few decades. Calendar time hypothesis is a process which operates continuously so that the return on Monday would represent a three-calendar-day investment; therefore, the expected return for Mondays would be three times the expected return for any of the other days of the week (French, 1980). The settlement period hypothesis has been found to explain some calendar effects across different markets in which returns have been higher on pay-in days compared to pay-out days (Raj & Kumari, 2006).

French (1980) extended Fama's (1965) contribution in which he examined whether the process of generating stock returns operates continuously or during active trading days only. This was done on S&P 500 stock returns with the following two methods - the Calendar-time hypothesis and the Trading-time hypothesis, in which the returns are only generated during the active trading days of the week. Therefore, if the alternative hypothesis was rejected, the returns for each day of the week should be identical since any of the returns represent only one trading day. French (1980) found that during the period 1953 to1977, the daily returns from the S&P 500 portfolio were inconsistent with both the Trading day model and the Calendar time model. The average returns on Mondays were negative compared to the other four positive trading day returns. This was an unusual finding, which led others to examine this anomaly further.

Gibbons & Hess (1981) further investigated into French's (1980) research as they examined the S&P 500 index and the equal weighted index for the period 1962 to 1978 for the day-of-the-week effect on asset returns. They considered the delay between trading and settlements in stocks and measurement errors as possible explanations for the day-of-the-week effect. They found a similar result to French (1980). However, Mondays were not the only day found to give significantly low mean returns. Tuesday appeared to also have low returns, and Wednesday and Friday had higher mean returns than Tuesday and Thursday. In the overall analysis, the annual mean return on a Monday ranged from -33.5% (S&P 500) to 26.8% (equally-weighted index). The hypothesis of the equality of means was rejected in each of the sub-periods run. The inclusion of the sub-periods was very valuable as it gave a different perspective of the market at different time periods.

Following Gibbons & Hess (1981), Rogalski (1984) developed his understanding of Monday returns further as he set out to examine the Dow Jones Industrial Average index (DJIA) in terms of trading day and non-trading day returns. This study was dissimilar from the previous papers as it distinguished between trading and non-trading day returns, in which the examination from Friday close to Monday close was decomposed into two parts, the first one being from Friday close to Monday open and the second one being

from Monday open to Monday close. He found that all of the average negative returns from Friday close to Monday close occur during non-trading hours and that the actual returns during Monday trading hours are positive.

Smirlock & Starks (1986) studied the nature and timing of the day-of-the-week effect on the Dow Jones Industrial Average. The use of hourly returns for a 21-year period was justified as more efficient and thorough in nature. For the empirical analysis, the total sample period was divided into three sub-periods. The first sub-period was from 1963 to 1968, the second was from 1968 to1974, and the last sub-period was from 1974 to 1983. In the pre-1974 periods, results showed that the hourly returns on Monday were significantly lower than the other trading days in the week. However, in the post 1974 period, there was nothing odd about Monday returns compared to the other trading days. To break this down further, the first sub-period showed that returns from Friday close to Monday open were positive. These returns were eliminated by the negative returns that occurred all day during Monday, resulting in a negative return for the entire day. In the second sub-period, the non-trading weekend returns were vaguely negative. This affected the opening hours of Monday in a negative manner and although the Monday returns did recover with the rest of the day showing positive returns, the returns for the entire day were significant and negative. For the last sub-period, the non-trading weekend returns were significantly negative. However, after noon, the Monday hourly returns were positive, yielding no weekend effect in trading time thus concluding that the weekend effect was 'moving up in time'. The results from the latter period were consistent with that of Rogalski (1984).

Several researchers focused primarily on the U.S. stock market for examining these anomalies. However, Jaffe & Westerfield (1985) decided to expand this research area and found evidence of this phenomenon in four other developed economies. They demonstrated that this irregularity wasn't just an element of the U.S. stock market. They observed that along with the US, Canada, UK, Japan and Australia had shown evidence of day-of-the-week effects. US, Canada and UK exhibited the lowest mean returns on a Monday, which is consistent with the literature so far. Contrary to the negative Monday returns, the lowest returns for Japan and Australia were found on Tuesday. This was an unexpected twist in their study, which led them to investigate further into this matter. They also confirmed that measurement errors and settlement periods were not the cause of the day-of-the-week effect. They tested whether the anomalies found in the other four economies was a result of the seasonality found in the US stock market. Results showed that there may have been some evidence of a one day time lag between the US and Australia. The time zone theory or the spill-over effect may have explained some of the seasonality in the Australian stock market.

Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) developed models to explain time-dependent patterns in security trading caused by the arrival of private information. Both studies demonstrated how information was incorporated into pricing and how various groups of investors influenced prices. Specifically, both Admati and Pfleiderer and Foster and Viswanathan took into account the roles of liquidity and informed traders in explaining variations in volume and volatility. Accordingly, traders would try to minimise their trading costs and therefore trade when the trading costs were lower (or liquidity was higher). The difference between Admati and Pfleiderer and Foster and Viswanathan models rested on the assumption about the trading patterns of informed and liquidity traders. While Admati and Pfleiderer model predicted that both informed and liquidity traders trade together, Foster and Viswanathan's model predicted that private information is short lived

and liquidity traders avoid trading with informed traders. The implications of these two models were as follows: Foster and Viswanathan proposed that liquidity traders avoid trading with informed traders when private information is intense. The resulting volume would be low and this would imply low volume comes with high volatility. Admati and Pfleiderer speculated that trading volume would be high when price volatility is high.

Rystrom and Benson (1989) suggested that investor psychology is one explanation for the market inefficiency. They suggested that although investors were assumed to be rational, at times they act irrationally, which in turn, would lead their economic decision making to be influenced by emotions and moods. If these emotions vary across the days of the week, it can very well generate high or low degree of optimism or pessimism across the days of the week. This would produce different returns across the days of the week. So if investors felt a high degree of pessimism on a Monday in comparison to any other day of the week, then they would sell their securities and depress prices. Conversely, investors would buy on Fridays if they felt more optimistic creating an upward pressure in security prices.

Pettengill (2003) gave a similar explanation as Rustrom and Benson (1989) as he believed that investors keep away from buying securities on Mondays because they are fearful of possible losses from trading with well-informed traders who may be selling their securities on Monday based on critical information they may have received over the weekend.

Turn-of-the-month effect

This effect is related to the temporary increase in stock prices during the last few days or the first few days of each month. Some of the research studies on the subject attribute the turn-of-the-month effect to the salary distribution in the last week or early in the first week of a month, which results in higher liquidity for investors. Some researchers also attribute it to distributions from pension funds and other retirement accounts that pensioners immediately reinvest in the stock market. According to turn-of-the month effect, the mean returns in early days of the month are higher than other days of the month.

Cadsby and Ratner (1991) examined the turn-of-the-month and pre-holiday effects on international markets. Turn-of-the-month effects are significant in Canada, UK, Australia, Switzerland and West Germany.

It was observed that the pre-holiday effects were significant in Canada, Japan, Hong Kong and Australia. The absence of these effects in certain markets suggested that they originated from country-specific institutional practices. According to them, all countries exhibiting pre-holiday effects do so before local holidays; only Hong Kong does so before US holidays. This led them to conclude that such anomalies are not generated solely by American institutions. They stated two reasons for considering international evidence on turn-of-the-month and pre-holiday effects. First, weekend effects and turn-of-the-year effects have been observed in a number of countries. They were of the view that it may be possible that these effects are being generated independently within each of these countries. The study considered that it may be possible that the effects are generated by US institutions alone and spread throughout the world by US investors trading on foreign markets. The study illustrated that as weekends and turn-of-the-year occur at the same time in all countries, it is difficult to distinguish between these two possibilities.

Kok and Wong (2004) reviewed the third-month anomaly in five ASEAN countries during the period of the ASEAN financial crisis in 1997. Third-month anomaly is basically when a particular month is divided

into three sections and returns in each of the sections are calculated and analysed. The first section incorporates returns from the 28th day of the previous month till the 7th day of the current month; the second section includes returns from the 8th day to 17th day of the month, and the last section includes returns from the 19th day till the 27th day of the month. Five ASEAN countries included in the data were: Malaysia, Singapore, Thailand, Indonesia and the Philippines. The period under study was from 1992 to 2002. During the pre-crisis period, all five countries presented different patterns of returns during different sections of the month. Malaysia, Indonesia and Philippines recorded highest average returns during the first section of the month whereas lowest returns were witnessed in the second section of the month by Malaysia and Indonesia.

Time-of-the-day effect

Mitchell (2017) stated that day traders require only the first one or two hours of the stock market for their trading activity. It is observed that the first hour of the stock market is considered to be the most volatile and thereby provides the most opportunity to make profits. According to his observation, professional traders know there is a lot of 'dumb' money flowing at this time. 'Dumb' money is created by people transacting based on what they perceive subsequent to going through secondary data. The traders act on stale information, which creates sharp price movements back and forth, as 'dumb' money flows push a stock (or the index) one way. Professional traders take advantage of this price push by pushing it back. For professional day traders, the first 15 minutes offer the maximum opportunity when several of the largest trades of the day are done based on initial trends.

Month-of-the-year effect

The month-of-the-year effect is a seasonal phenomenon where exchange traded equities tend to produce abnormal returns during particular months of the year. The January effect is a special case of the 'month-of-the-year effect' and relates to the seasonal increase in stock prices during the month of January. Investors and analysts generally attribute this rally to an increase in buying, which follows a drop in price that typically happens in December when investors, engaging in tax-loss harvesting to offset realised capital gains, prompt a sell-off. Another possible explanation is that investors use year-end cash bonuses to purchase investments on the following month. This effect reflects variations in returns of different months in a year (Gultekin & Gultekin 1983). January returns are greatest due to year-end tax loss selling of shares disproportionally (Branch 1977). The general argument for the January effect was supposedly attributed to tax-loss hypothesis. Investors sell in December and buy back in January.

Since 1942, old and new calendar anomalies like the January effect (Cooper et al, (2006)) and seasonal effects in the cross section of the stock returns (Heston & Sadka, (2007)) kept practitioners and academics intrigued.

Wachtel (1942) uncovered the January effect in the US stock market. He documented a sample period from 1928 to 1940. He proposed that the five possible causes of the January effect were 1.) tax loss selling; 2.) unusual cash demand around Christmas; 3.) a pre-Christmas holiday effect; 4.) the anticipation of better business in the spring; and 5.) a positive new feeling about the coming new year.

Rozeff and Kinney (1976) investigated the presence of seasonality in the US markets. Their study made the January effect popular among academicians wherein they used a relatively long sample of 70 years of NYSE index data from 1904 to 1974. Using an equal-weighted index of NYSE prices, they reported

evidence of a seasonal pattern in stock market returns. From 1904 to 1974, the average stock market returns during the month of January was 3.48% whereas the monthly return during the remaining 11 months of the year was 0.42%. January returns appeared to be more than eight times higher than returns for a typical month. As the equal-weighted NYSE index embodied a simple average of the stock prices for all listed companies, Rozeff and Kinney's methodology gave small companies greater relative influence than would be true in a value weighted index, where large companies dominated.

Brown et al, (1982) carried out a study on Australian stocks for the period 1958 to 1981 and found that they exhibit higher returns not only in July (which was aligned with tax loss selling as the fiscal year ends in June), but also in December, January and August.

Gultekin & Gultekin (1983) studied the monthly data of value weighted stock market indices of 17 industrialised countries from 1959 to 1979. They inferred the presence of the January effect in all 17 countries and an April effect for the UK market. As the tax year ends on April 5 in the UK, an April effect was consistent with the tax loss hypothesis. With the only exception of Australia, their observations were in support of the tax loss selling hypothesis.

Research by Berges et al. (1984) exhibited that the January effect in the Canadian market was present both before and after the introduction of capital gains tax in 1973 using data for a period of 30 years from 1950 to 1980.

Van den Bergh & Wessels (1985) found the January effect in the Dutch stock market for the period 1966 to 1982 even though capital gains were not taxed. In spite of the fact that individual investors were not subjected to capital gains taxes in Japan and the corporate fiscal year end varied amongst firms, Kato and Schallheuim (1985) observed both a January and a June effect for the Japanese stock market from 1952 to 1980. Their study persuaded supporting both the alternative liquidity and information hypotheses.

The tax-loss selling explanation subsequently became the most widely investigated hypothesis especially after Keim (1983) showed the January effect in the US market to be size related and concentrated primarily in the small firms. Reinganum (1983) and Roll (1983), Schultz (1985), Jones et al, (1991), Poterba & Weisbenner, (2001); Starks, Yong and Zheng (2006) confirmed that the January effect was a small-capitalisation phenomenon. The research could not rule out the validity of other alternative clarifications such as the liquidity hypothesis, window dressing optimistic expectations, and the information hypothesis.

Tinic et al. (1987) established no seasonality in stocks traded by foreign investors and Canadians who were subjected to taxation before 1972, indicating that tax loss selling cannot fully explain the January effect.

Jones et al. (1987) demonstrated that the January effect was present long before income taxes in the US, which contradicts the tax loss selling hypothesis.

Reinganum & Shapiro (1987) studied the UK stock market using monthly data from 1955 to 1980; their research supported the tax loss selling hypothesis. They documented both the January effect and April effect after the introduction of capital gain taxes in April 1965, although they detected no seasonality in the pre-tax period. They assumed that the January effect may be due to the international stock market integration. They also suggested that the January effect in the UK stock market is determined by corporations which have a tax year ending at the end of December.

Lakonishok & Smidt (1988), in their seminal study, suggested long and new data series as the finest medicine against boredom (selection bias), noise and data snooping. They confirmed several daily anomalies like the turn-of-the-week effect, the turn-of-the-month effect, the turn-of-the-year effect and the holiday effect in their extended sample of 90 years of the Dow Jones Market Index. According to them, monthly data offered a good illustration of Black's (1986) view about the trouble of testing hypothesis with noisy data. It is fairly possible that certain months were undeniably unique, but even with 90 years of data, the standard deviation of the mean monthly return was very high (around 0.5%). Hence, unless the unique month outperforms other months by more than 1%, it would not be identified as a special month.

Odegan (1990) argued that the January effect stems from the amplified demand for stocks triggered by the liquid cash injection from year-end bonuses, salaries and dividend payments.

Ho (1990) conducted a study in the emerging market and confirmed the presence of the January effect in 7 out of 10 Asia Pacific markets.

Choudhary (2001) reported evidence of the January effect in both the US and the UK market for the period 1870 to 1913.

Clare et al. (1995) documented high December returns and low September returns in the UK stock market during the period 1955 to 1990.

Dimson and Marsh (2001) applied the cross sectional data across the UK markets and concluded that the January effect was a market wide phenomenon, unlike in the US, where the irregularity in these countries was not related to firm size. Brown et al. (1982) conducted a similar study for the Australian markets and concluded the same.

Fountas & Segredakis (2002) investigated monthly seasonality in 18 emerging markets and established a significant January effect in Chile, Greece and Turkey, comparatively high December returns in Malaysia and Colombia and low October returns in Greece.

Odgen (2003) related equity return patterns to the seasonality of macroeconomic variables. Odgen and Fitzpatrick (2010) showed that several anomalies such as the failure-earnings momentum, risk anomaly, and the book-to-market anomaly may be attributed to seasonality.

Raj and Kumari (2006) did not find positive January effects in India.

Anderson et. al. (2007) examined the US market and suggested behaviourally related explanations supported by laboratory tests. They controlled for variables that could influence subject bids such as variances in private values, cumulative earnings and the learnings effects. They observed that the prices in the January markets were systematically higher as compared to December. They confirmed a difference, which was economically large and statistically significant. The inferences provided support for the supposition that psychological issues may contribute to the January effect.

Sutheebanjard and Premchaiswadi (2010) examined the day-of-the-week effect on the Stock Exchange of Thailand (SET) by using the daily SET Index data of 1,040 days from 4 January 2005 to 31 March 2009.

They documented that day-of-the-week had a substantial effect on the SET index with the maximum percent of prediction error on Monday and the lowest percent of prediction error on Friday.

Dodd and Gakhovich (2011) found abnormal returns on days prior to holidays on various markets around

the globe which was against the EMH.

Darrat et al. (2011) studied the monthly seasonality in 34 equity markets including the US and the UK. Applying a more recent sample period from 1988 to 2010, they observed an absence of the January effect in all except 3 countries in the sample (Denmark, Ireland and Jordan). Also, several stock markets revealed significantly higher returns in April and December, and lower returns in June, August and September.

Marret and Worthington (2011) conducted a study on the Australian stock market to gauge the month-of-the-year effect using a regression-based approach. The results of the month-of-the-year regressions indicated significantly higher returns in April, July and December. The mean return of the 'All Ordinaries Index' on any given day of the year was 0.0288%. The mean daily returns in April, July and December were 0.0846%, 0.0670% and 0.0956% respectively. Conversely, the 'Small Ordinaries index' displayed a significant January effect. The mean return of small cap firms over the sample period was 0.0160%, whereas the mean return in January was 0.0853%. August (0.0631%) and December (0.0790%) also displayed significantly higher returns than other months of the year. A likely explanation for the small cap effect was supposedly due to the portfolio rebalancing hypothesis as portfolio re-balancing is common at the turn of the year.

Ciccone (2011) suggested the optimistic expectation hypothesis. He claimed that the turn-of-the-year is the time of renewed optimism that bids up the stock prices in January.

Research by Casado, Muga and Santamaria (2013) reported abnormally high returns on European indices during US Holidays, which are trading days in Europe. The paper investigated five European indices for the period 1991 to 2008 and observed evidence of the anomaly specified to "consist of the existence of substantial positive returns in European stock markets on days when the NYSE had a leave". They discovered a significant effect that existed after controlling for other seasonal anomalies and the preceding day's inertia from the European markets and the US market. The outcomes are robust with US holidays carrying an average return of fifteen times an average trading day with below-average risk, and the anomaly offered profits from trading even after accounting for the transaction costs. The impact was significant when the NYSE closed positive on the day before although not significant on a day subsequent to a negative close on the NYSE.

There were two explanations given for this effect; firstly, that the US markets form a large segment of the financial news in the world and hence, lesser information flows on a US holiday, and secondly, fewer investors were active due to the withdrawal of US investors. This supposedly would increase noise trader risk owing to a higher share of noise traders matched to the sophisticated investors according to De Long et al. (1990). Lesser information flow coupled with the withdrawal of US investors would lead to fewer investor disagreements and thereby would result in lower volumes and lower returns, which happens to be very much in accordance with the disagreement model documented by Hong and Stein (2007). Subsequently, due to the withdrawal of the investors and lesser flow of new information on the US holidays, volumes were anticipated to be lower as compared to an average day, which conferring to the disagreement model, implicated lower returns. However, the principle on noise trading establishes that as the proportion of noise traders intensifies, prices would deviate from their fundamental values and the returns would be positive on an average basis.

Gouider, Kaddour and Hmaid (2015) examined the

impact of financial market anomalies, specifically calendar anomalies, on the behaviour of investors in terms of decisions and profit. They evaluated the Tunisian financial market by breaking up the data into two periods in terms of two different political regimes. They examined the weekend consequences, the end-of-the-month effect, the January outcomes and Ramadhan impact. The stock market returns based on a GARCH specification indicated that most of the anomalies exist on the Tunisian stock market; the weekend effect was confirmed and they observed a yield dissimilarity between the beginning of the week (low and negative returns) and the end of the week; this disparity is affected in terms of significance between the two periods under diverse political establishments. The impact of the holy month was twice higher in comparison to the rest of the year.

Methodology

The study investigates the existence of market anomalies with respect to Nifty 50 from January 1997 to December 2016. The motivation to choose the Nifty 50 index was that in the Indian context, bulk of the investments is made in this index as compared to other indices. The price return data has been taken from Thomson Reuter's Data stream and consists of daily and monthly closing values for the period. Daily returns, average returns per month, and average returns per day for all 20 years were tabulated for analysis. A longer historical period was taken for the study in order to capture majority of market fluctuations due to various stress scenarios including all the financial/economic crises.

EMH is of the premise that past price behaviour leads to zero probability to predict changes in the stock prices and an inability for any investor to generate super normal profits based on the same. However, there are certain opportunities in the stock markets which can be utilised to generate alpha returns. This study attempts to understand these types of trends, which occur in the share markets and are generally referred to as calendar anomalies.

This study investigates the existence of various variants of calendar anomalies like the day-of-the-week effect, month-of-the-year effect, turn-of-the-month effect, and January effect in the Indian equity markets.

For evaluating whether any of these anomalies exist, the daily and monthly price returns were calculated by applying the following formula:

Return = R_t = (Pt / P(t-1)) x 100)

Where P (t) refers to price of the relevant index on day or month t and P(t-1) refers to a day before that.

The T-test was applied whose statistical significance indicates whether or not the difference between two groups' averages most likely reflects a “real” difference in the population from which the groups were sampled.

Two further tests were applied to test the anomalies: ANOVA and the GARCH class of models.

The empirical approach undertaken for testing the anomalies are discussed below:

Day-of-the-week effect

The following model equation to test the day-of-the-week effect was applied. For example, for a specific day, the daily return for that day (Monday, Tuesday etc…) was taken and a dummy variable was created for other days so as to compare return patterns for all days. The author has assumed that there are zero transaction costs.

$$R_t = x_0 + x_1 d_1 + x_2 d_2 + x_3 d_3 + x_4 d_4 + e_t$$

where

R_t = the return on day t;

x_n = the mean return for each day of the week;
d_1 through d_4 = the dummies used for day-of-the-week that are either 0 or 1 (d_1= 1 for Monday and 0 otherwise and so on);
e_t = the random error term for day t.

The null hypothesis for the day-of-the-week effect is - (Ho): x1 = x2 = x3 = x4
If this hypothesis is rejected, it would imply that the mean daily returns x_n are significantly different from each other, which will prove that there exists seasonality in returns across different days of the week in the study period.

Month-of-the-year effect

The following model equation was applied to test the month-of-the-year effect.

For example, for a specific month, the monthly returns for that day (January, February etc...) were taken and a dummy variable was created for other months so as to compare return patterns for all the months:

$R_t = x_0 + x_n d_{nt} + e_t$
where
R_t= the monthly return in month t
x_0= expected monthly return
x_i= mean return for the nth month
d_{nt}= dummy variable for months of the year and 0 or 1 (d2t = 1 for February and 0 otherwise and so on)

The Null hypothesis (Ho) for testing this effect will be:
$x_2 = x_3 = \ldots = x_n$
If this hypothesis is rejected, it implies that return for that month is significantly different from other months of the year. An extension of this effect is the January effect for which the same approach is applied.

Turn-of-the-month effect

The following model equation was applied to test the turn-of-the-month effect.

For example, for a specific month, the last day of the month and the first three days of the next month were taken, and the return pattern for all those days was compared.
A four-day (-1, +3) window was taken and the following regression equation was applied:

$R_t = \beta_0 + \beta_1 d_{2t} + \varepsilon_t$
where
R_t is the mean return for the day t
d_{it} is dummy variable for the effect
β_i is the coefficient for the mean return
ε_t is the error term

Significant positive value of coefficient β_1 would demonstrate the turn-of-the-month effect.

ANOVA for the daily return was used to examine whether there was any statistically significant difference between the means and the p-value, which was compared to the significance level to assess the null hypothesis. A significance level of 0.05 was employed for the comparison.

Results

Day-of-the-week effect – ANOVA

Null hypothesis = H_0: The average daily return of every working day of the week was statistically equal.

Table 1: Nifty day-of-the-week ANOVA

Summary

Groups	Count	Sum	Average	Variance
Monday	983	(5.341)	(0.005)	0.034
Tuesday	987	(13.769)	(0.014)	0.020
Wednesday	983	229.646	0.234	0.022
Thursday	986	17.266	0.018	0.020
Friday	964	43.991	0.046	0.026

Source: Author's research findings

Table 2: ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.004	4	0.001	4.205	0.002	2.374
Within Groups	1.197	4898	0.000			
Total	1.201	4902				

Source: Author's research findings

As observed from Table 1, aggregate returns for Wednesday were substantially the highest (~229%). Monday and Tuesday displayed negative returns. Average returns for Wednesday (0.234%) were also higher than any other day in the week and significantly above that of negative returns of Monday and Tuesday. The p-value from the ANOVA table (0.002) was below the significance level and thus, the model is statistically significant. Therefore, the null hypothesis is rejected and it was concluded that the day-of-the-week effect was established to be relevant for Nifty 50.

Day-of-the-week – Regression

Null hypothesis = H_0: The average daily return of every working day of the week was statistically equal.

Table3: Regression Output: Day of the Week Effect

		NIFTY		
Variable	**Coefficients**	**Std. Error**	**t-Statistic**	**P-value**
MONDAY	(0.000)	0.001	(0.716)	0.474
TUESDAY	(0.001)	0.001	(0.837)	0.403
WEDNESDAY	0.002	0.001	2.678	0.007
THURSDAY	(0.000)	0.001	(0.389)	0.697
FRIDAY	0.000	0.000	0.902	0.367
F-Stat 4.214; p-value 0.002				

Source: Author's research findings

Month-of-the-year – ANOVA

Null hypothesis = H_0: The average monthly return of every month of the year was statistically equal.

Table 4: Nifty month-of-the-year (ANOVA)

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
January	20	72.302	3.615	0.343
February	20	(28.021)	(1.401)	0.502
March	20	48.413	2.421	0.418
April	20	(2.871)	(0.144)	0.643
May	20	5.189	0.259	0.449
June	20	17.198	0.860	1.160
July	20	41.420	2.071	0.544
August	20	24.535	1.227	0.373
September	20	14.936	0.747	0.451
October	20	43.630	2.181	0.563
November	20	(2.260)	(0.113)	0.831
December	19	48.692	2.563	0.469

Source: Author's research findings

Table 5: ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.045	11	0.004	0.721	0.718	1.831
Within Groups	1.277	227	0.006			
Total	1.322	238				

Source: Author's research findings

Results for Nifty 50 indicated that the average monthly returns were positive except for the months of February, April and November. Average monthly returns for January (3.6%) were substantially higher than other months. However, the comparison of the p-value with the level of significance (0.05) suggested that the model is statistically insignificant and therefore, the null hypothesis is not rejected. It was inferred that the month-of-the-year effect was not seen in Nifty 50.

Month-of-the-year – Regression

Null hypothesis = H_0: The average monthly return of every month of the year was statistically equal.

Table 6: Regression Output: Month-of-the-year effect

	Nifty			
Variable	**Coefficients**	**Std. Error**	**t-Statistic**	**P-value**
January (Intercept)	0.024	0.017	1.451	0.148
February	0.014	0.024	0.575	0.566
March	(0.038)	0.024	(1.617)	0.107
April	(0.000)	0.024	(0.005)	0.996
May	(0.026)	0.024	(1.087)	0.278
June	(0.022)	0.024	(0.917)	0.360
July	(0.016)	0.024	(0.664)	0.508
August	(0.004)	0.024	(0.152)	0.879
September	(0.012)	0.024	(0.509)	0.611
October	(0.017)	0.024	(0.711)	0.478
November	(0.003)	0.024	(0.106)	0.916
December	(0.025)	0.024	(1.074)	0.284
F-Stat 0.735; p-value 0.705				

Source: Author's research findings

Intercept coefficient gave average returns of 0.02% for January with reference to Nifty 50. The January month return was the highest in Nifty 50; almost all variable coefficients were observed to be negative and none of them were found to be statistically significant. Comparing the p-value for Nifty, the model was statistically insignificant at 5% confidence level. Although absolute monthly returns were different from each other, results of ANOVA and multiple regression indicated that month-of-the-year effect is not observed in Nifty 50.

Turn-of-the-month: ANOVA

Null hypothesis = H_0: Return of turn-of-the-month (-1, +3) days and other days was statistically equal.

Table 7: Nifty turn-of-the-month ANOVA

Summary

Groups	***Count***	***Sum***	***Average***	***Variance***
Turn-of-the-month	5200	207.816	0.040	0.004
Other days	5200	63.987	0.012	0.019

Source: Author's research findings

Table 8: ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.000	1	0.000	1.721	0.040	3.842
Within Groups	1.202	10398	0.000			
Total	1.202	10399				

Source: Author's research findings

Comparing the results of ANOVA test between returns of turn-of-the-month (-1, +3) days and other days of the month, p-values Nifty indicated that the model is significant at 5% confidence level. Thereby, it was established that these means are significantly different from each other and turn-of-the-month effect was observed in Nifty 50.

Table 9: Regression Output: Turn-of-the-month

		Nifty		
Variable	**Coefficients**	**Std. Error**	**t-Statistic**	**P-value**
Turn-of-the-month	0.002	0.001	3.719	0.000
Other days	0.000	0.000	0.648	0.517
F-Stat 13.83; p-value 0.0002				

Source: Author's research findings

The intercept coefficient indicated the average return of 0.002% for turn-of-the-month (-1, +3) days with reference to Nifty 50. As the p-values of Nifty 50 were below the significance level, it indicates that the model was statistically significant at 5% confidence level. Thus, it was derived that the turn-of-the-month effect was significantly observed in Nifty 50.

January effect ANOVA

Null hypothesis = H_0: The average monthly return of January month-of-the-year was statistically equal to other months.

Table 10: Nifty January effect ANOVA

Summary

Groups	*Count*	*Sum*	*Average*	*Variance*
January	20	72.302	3.615	0.343
February	20	(28.021)	(1.401)	0.502
March	20	48.413	2.421	0.418
April	20	(2.871)	(0.144)	0.643
May	20	5.189	0.259	0.449
June	20	17.198	0.860	1.160

Groups	Count	Sum	Average	Variance
July	20	41.420	2.071	0.544
August	20	24.535	1.227	0.373
September	20	14.936	0.747	0.451
October	20	43.630	2.181	0.563
November	20	(2.260)	(0.113)	0.831
December	19	48.692	2.563	0.469

Source: Author's research findings

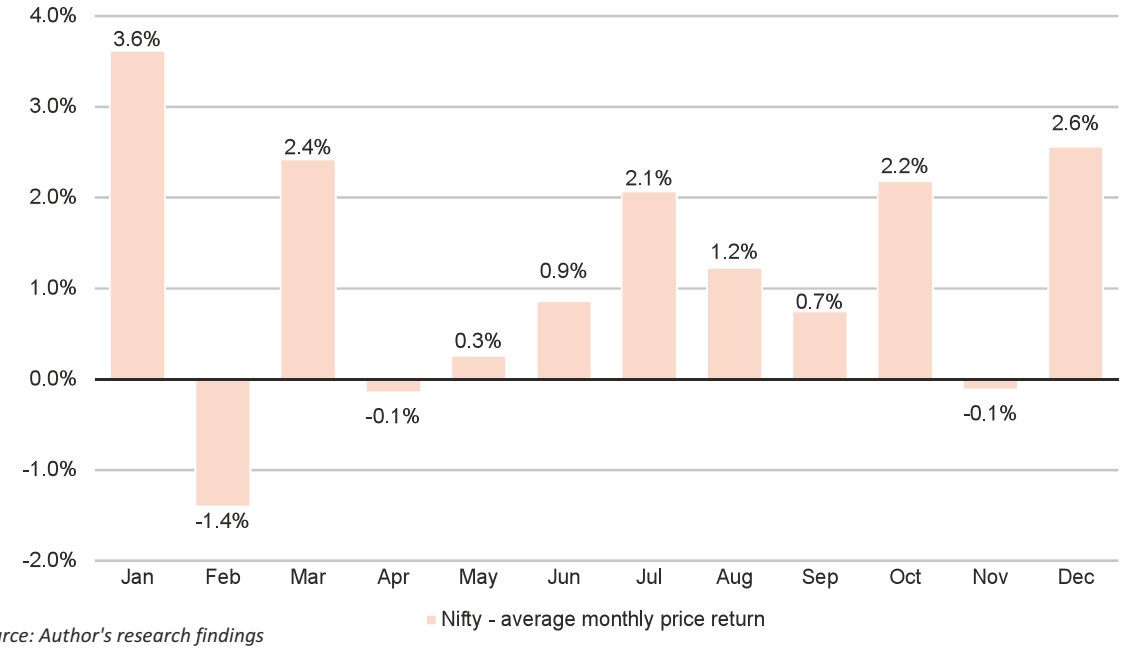
Table 11: ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.045	11	0.004	0.721	0.718	1.831
Within Groups	1.277	227	0.006			
Total	1.322	238				

Source: Author's research findings

The average monthly returns of Nifty 50 were positive except for the months of February, April and November. Average monthly returns for January (3.6%) were substantially higher than other months. However, the comparison of the P-value with the level of significance (0.05) suggested that the model was statistically insignificant and therefore, the null hypothesis was not rejected. Therefore, an average return of January was not significantly different from other months. Thus, the January effect was not exhibited by Nifty 50.

Figure 1: For Nifty, January has the highest average monthly returns during 1997-2016



Source: Author's research findings

January effect Regression

Null hypothesis = H_0: The average monthly return of January month-of-the-year was statistically equal to other months.

Table 12: Regression Output: January effect

	Nifty			
Variable	**Coefficients**	**Std. Error**	**t-Statistic**	**P-value**
January (Intercept)	0.024	0.017	1.451	0.148
February	0.014	0.024	0.575	0.566
March	(0.038)	0.024	(1.617)	0.107
April	(0.000)	0.024	(0.005)	0.996
May	(0.026)	0.024	(1.087)	0.278
June	(0.022)	0.024	(0.917)	0.360
July	(0.016)	0.024	(0.664)	0.508
August	(0.004)	0.024	(0.152)	0.879
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October	(0.017)	0.024	(0.711)	0.478
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December	(0.025)	0.024	(1.074)	0.284
F-Stat 0.735; p-value 0.705				

Source: Author's research findings

Intercept coefficient gave average returns of 0.02% for January with reference to Nifty 50. It was the highest in Nifty 50 wherein almost all variable coefficients were observed to be negative and none of them were statistically significant. Comparing the p-value for Nifty 50, the model was statistically insignificant at 5% confidence level. Although, January's absolute returns are different from other months, results of ANOVA and multiple regression exhibits that January effect was not observed in Nifty 50.

Conclusion

The purpose of this study was to scrutinise the existence of calendar anomalies in the Indian stock market for the period ranging from January 1997 to December 2016. The major objective of this study was to determine whether stock returns on any particular day-of-the-week, month-of-the-year, and turn-of-the-month or January effect were significantly different from the average returns on rest of the periods on the NSE.

The study concluded that Nifty exhibits day-of-the-week effect and turn-of-the-month effect to a substantial extent. According to this study, the average return for the turn-of-the-month days was substantially higher (0.04% for Nifty) versus rest of the days of the month (0.012% for Nifty). This illustrated that there was potential for investors to create superior returns in the turn-of-the-month days.

The plausible motivation for higher returns on these days or the overall turn-of-the- month effect may be primarily justified by the behavioural aspect of investors. Investors tend to sell their shares at the end of the month and expect a positive change in the next month due to release of new information at the end or at the start of the new month. As such, investors get maximum benefit by selling at the end of the month and repurchasing at the start of the new month.

Day-of-the-week effect was seen in Nifty 50. The index exhibits substantially higher daily returns for Wednesday (0.234%) which was higher than any other day in the week and significantly above that of negative returns of Monday and Tuesday. This phenomenon may be associated with the fact that the investors may be more cautious at the beginning of the week and wait for information to trigger the investment sentiment.

Month-of-the-year effect did not exist in Nifty 50. For Nifty 50, January showed an average return of 3.6% as compared to 2.4%, 2.2% and 2.6% for March, October and December respectively. According to the statistical data, no month could be singled out to give substantial returns consistently. The statistical data established that the January effect was not observed in Nifty 50.

The outcomes of this study established that there are patterns in the Indian stock market, which could be exploited to generate above-normal returns and the markets do not adhere to the Efficient Market Hypothesis (EMH). The study asserts that anomalies do exist in the market and investors may improve their returns by timing their investments according to these anomalies. Moreover, the patterns observed in the Indian stock market vary from other developed markets, and provide an opportunity for Foreign Institutional Investors (FIIs) and domestic investors to achieve maximum profits.

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