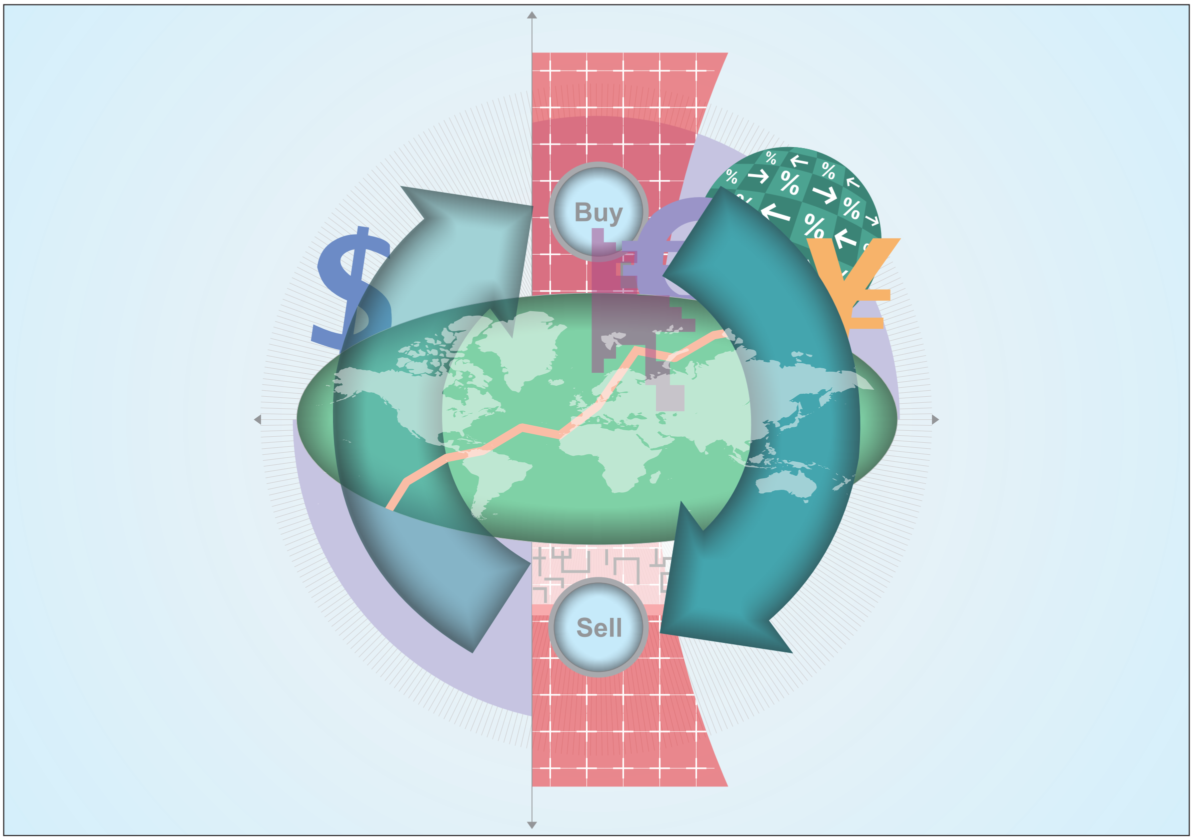

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Month of the Year Anomalies in Stock Markets: Evidence from India

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ABSTRACT

Judging the importance of existence of calendar anomalies in the stock market to the investors, the present study attempts to find out monthly anomalies in the market. The presence of seasonal effects in monthly returns in the Indian market has been reported by many researchers in the past. This study attempts to examine whether the month-of-the-year anomaly still exists in the Indian Stock Market. For this purpose, two indices, S and P CNX Nifty and S and P CNX Nifty Junior and top nine companies (according to market capitalisation) from both the indices have been selected. The daily closing prices of the respective indices and stocks have been taken and the logarithm return of these prices has been calculated. Line charts and unit-root test are applied to check the stationary nature of the series. The Dummy Variable Regression Model has been applied on the returns to find out any statistically significant deterrent month in the year. The present study observes that both the indices and some of the selected companies reflect the month-of-the-year anomalies in the Indian Stock Market. Mainly, the monthly anomaly is found at the end of a quarter for the given period.

Key words: Nifty, nifty junior, market capitalization

INTRODUCTION

Efficient Market Hypothesis (EMH) claims that in an efficient market stock prices always fully reflect available information and therefore, it is impossible to beat the market because prices already incorporate and reflect all relevant information. According to Malkiel (2003), the efficient market hypothesis is associated with the idea of a "Random walk" which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departures from previous prices. However, advances in Behavioural Finance over the last several decades appeared to have shifted the paradigm away from the EMH theory. Several market anomalies, contradicting the EMH, have been reported, such as fundamental, technical and calendar anomalies. They are called anomalies because they cannot be explained by traditional asset pricing models and they violate the market efficiency. One of the most discussed anomalies phenomenon is seasonality effect or the calendar anomalies. There exist several seasonal anomalies which involve patterns in stock returns such as the month-of-the-year effect, the day-of-the-week effect, the turn-of-the-month effect, the mid-month effect, the intra-month effect, the holiday effect, the daylight savings effect and many others. The existence of the seasonal effect negates the weak form of the EMH and implies market inefficiency by the predictable movements in asset prices providing investors with opportunities to generate abnormal returns. Such market anomalies are primarily due to behavioural causes. The presence of market anomalies seems to be ubiquitous, occurring in stock markets around the world, in both developed and emerging markets. The investigation of calendar patterns or seasonality in stock market returns is certainly a classic study in the field of finance. These seasonal anomalies have attracted much interest among both financial scholars and practitioners. Numerous researchers have studied calendar anomalies in financial markets and a great deal of portfolio managers makes use of this theory in real market scenario.

One of the most commonly studied market anomalies is the month-of-the-year effect, wherein return in a particular month is deferent from other months and such a variation is statistically significant. 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 most prevalent manifestation or the most studied pattern of the monthly effect in the stock market is the so called 'January Effect'. It is established that in January, the stock return is higher than that of other months of the year. It may be caused normally by a significant low return in December. According to Ritter (1988), the ratio of stock purchases to sales of individual investors reaches an annual low at the end of December and an annual high at the beginning of January. The concept has been debated widely for decades with different caveats proposed around small-cap stocks or large caps, wash-sale rules, liquidity and trading costs.

The existence of the month-of-the-year effect holds important implications for the markets and investors. If month-of-the-year effect existed in stock returns, investors might be enable to take advantage of relatively regular patterns in the market by designing trading strategies which accounts for such predictable patterns.

The question of efficiency of the Indian stock markets is not a novel undertaking. Pandey (2002) confirmed a tax-loss-selling hypothesis in the Indian market explaining the presence of abnormal returns in April only to be contradicted later by various other studies. Dash *et al.* (2011) also provided evidence for monthly anomalies in the Indian Stock Market. Nageswari and Selvam (2011), however, concluded that the Month-of-the-year effect pattern does not exist in Indian Stock Market.

The above reflect a somewhat controversial picture of the Indian stock market over the years, maybe due to statistical misgivings. Or perhaps we could presume the disappearance of these anomalies over time as in Schwert (2002), on the basis that rational traders exploit the documented anomalous behaviour, hence leading to more efficient markets. In other words, the anomalies are arbitraged away.

The existence of the month-of-the-year effect holds important implications for the markets and investors. If month-of-the-year effect existed in stock returns, investors might be enable to take advantage of relatively regular patterns in the market by designing trading strategies which accounts for such predictable patterns.

The present study aims at the following objectives:

- To investigate whether there exists a month-of-the-year effect in NSE's indices: S and P CNX Nifty and S and P CNX Nifty Junior
- To test the presence (or absence) of month-of-the-year effect in the top nine companies (according to market capitalisation) of both the above indices
- To establish if the Indian Stock Market investors may get abnormal returns by studying and applying month-of-the-year effect

A lot of prior research has been done across the Asian countries. Balaban (1995), Balaban and Bulu (1996), Pandey (2002), Sarma (2004), Kling and Gao (2005), Guo and Wang (2007), Rahman (2009), Garg *et al*. (2010), Dash *et al*. (2011), Nageswari and Selvam (2011), Chia and Liew (2012), Debasish (2012), Ahsan and Sarkar (2013), Nageswari *et al*. (2013), Pathak (2013), SiamiNamini *et al*. (2013) and Safeer and Kevin (2014) studied the seasonality in the secondary markets of the Asian countries.

Across the Asian countries, India has been a common geographical area for studying the seasonality in the stock market returns among the researchers. Pandey (2002) studied the existence of seasonality in India's stock market. It covered the post-reform period. The study used the monthly return data of Bombay Stock Exchange's Sensitivity Index for the period from April 1991 to March 2002 for analysis. Sarma (2004) also studied the Indian Stock Market from January, 1996 to August 2002. Dash *et al*. (2011) focused on the monthly patterns of returns in the Indian stock market, specifically the Bombay Stock Exchange (BSE). The data used for the study were the monthly closing Sensex values in the period April 1999 to March 2007. Nageswari and Selvam (2011) also investigated the existence of seasonality in India's stock market. Their research was based on the data of Bombay Stock Exchange (BSE) Sensex for a period of 10 years from April 2000 to March 2010. Debasish (2012) studied the existence of seasonality in stock price behavior in Indian stock market and more specifically in the Gas, Oil and Refineries sector over a time period of 5 years from January 2006 to December 2010. Nageswari *et al*. (2013) used the logarithmic data for S and P CNX Nifty and S and P CNX 500 sample indices from April 2002 to March 2011. Pathak (2013) examined stock market seasonality effect for the S and P CNX Nifty Index over the period from April 2002 to March 2012. Safeer and Kevin (2014) also studied the market anomalies across the Indian Stock Market by comparing averages of the mean of the values of BSE index from the year Jan 2008 to Dec 2012.

Other Asian Countries where the researchers studied the market anomalies include Bangladesh, China, Iran, Japan and Turkey. Ahsan and Sarkar (2013) studied the stock market anomalies in Dhaka Stock Exchange (DSE), Bangladesh from January 1987 to November 2012. Another researcher, Rahman (2009) also examined the presence of seasonality across the stock market returns in Dhaka Stock Exchange. For this purpose, he used the stock market data from September 2005 to October 2008. Kling and Gao (2005) studied the calendar effects in the Chinese Stock Market. They used the market indices of the Shanghai and Shenzhen stock exchanges for a period of 13 years from 1990 to 2002. Guo and Wang (2007) also studied the seasonality in the Chinese Stock Market using Shanghai Stock Exchange Composite Index. They covered a period of 15 years from 1992 to 2006. SiamiNamini *et al*. (2013) examined time-varying effectiveness of Stock Returns on Tehran Stock Exchange, Iran spread over a time span of 6 years from March 2004 to March 2010. Chia and Liew (2012) investigated the existence of seasonality and volatility in Japan stock market by using the Nikkei 225 index over the period from January 2000 to June 2009. Balaban (1995) and Balaban and Bulu (1996) examined the presence of stock market anomalies in the Turkish Stock Market using Istanbul Securities Exchange Composite Index (ISECI). Balaban (1995) covered a period from January 1998 to august 1994 while Balaban and Bulu (1996) performed their study covering a period from January 1988 to June 1995.

Sewraj *et al*. (2010), Agathee (2010), Nyamosi (2011), Kuria and Riro (2013) and Darrat *et al*. (2013) studied the anomalies of the African countries. Sewraj *et al*. (2010) studied the calendar effects on market returns in the Stock Exchange of Mauritius (SEM) in order to get the information whether the market anomalies exist or not. They covered a time span of 10 years from January

1998 to December 2008. Agathee (2010) also studied the market anomalies in the Mauritian official stock market using the data from August 2006 to May 2009. Nyamosi (2011) and Kuria and Riro (2013) studied the seasonal effects of stock market at the Nairobi Stock Exchange, Kenya. While, Nyamosi (2011) covered a period from 2001-2010, Kuria and Riro (2013) covered a time span of 12 years. Darrat *et al.* (2013) investigated the existence of seasonality of the Johannesburg Stock Exchange (South Africa) daily returns from January 1973 to September 2012.

Marrett and Worthington (2011) examined the presence of seasonality across the Australian stock market returns. Twelve different stock indices were used for this purpose. Each index series started on 9 September 1996 and provided 2,635 end-of-day observations on the Australian Stock Exchange (ASX).

Aly *et al.* (2004), Kolahi (2006), Camilleri (2008), Silva (2010) and Stefanescu and Dumitriu (2013) examined the market anomalies in the European continent. Aly *et al.* (2004) studied the seasonality in the major Egyptian Stock Market Index, the CMA Index from April 1998 to June 2001. Kolahi (2006) examined the seasonality in stock market returns of MSCI Europe Index which consists of 16 developed countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. Camilleri (2008) tested the presence of market efficiency in the Malta Stock Exchange covering a period from June 1998 to August 2005. Silva (2010) studied the calendar anomalies in the Portuguese Stock Market from May 1989 to December 2008. Finally, Stefanescu and Dumitriu (2013) studied the Romanian Capital Market for any inefficiencies in their stock market returns for two periods of time: 2000-2006 and 2006-2012, i.e., before and after the adhesion to European Union, respectively.

French (1980) and Li (2013) studied the capital market anomalies in the North American countries. French (1980) studied the stock market returns and the market anomalies in the United States of America using the Standard and Poor's composite portfolio from 1953 to 1977. Li (2013) on the other hand, studied the market inefficiencies in the financial services industry in Canadian market covering a period from January 2003 to December 2012.

Garg *et al.* (2010) studied the seasonal anomalies in stock returns of developed and emerging markets. For this purpose, the Indian and US markets were taken as the representative of emerging and developed markets, respectively. The reference period of the study ranged from January 1998 to December 2007.

Among the most popular calendar anomalies in the financial market are: month-of-the-year, day-of-the-week, turn-of-the-month and mid-month effects. Monthly effect implies that the mean return for stock depends upon the month of the year there is. The day-of-the-week effect involves patterns in stock returns on the last days related to, in particular, special days in a week. And finally, semi-monthly (intra-month) effect reflects the changes in return within a month as the days elapse.

Pandey (2002), Dash *et al.* (2011), Nyamosi (2011), Marrett and Worthington (2011), Chia and Liew (2012), Debasish (2012), Li (2013), Ahsan and Sarkar (2013), Nageswari *et al.* (2013) and Stefanescu and Dumitriu (2013) examined the presence of monthly effect in stock market returns. French (1980), Balaban (1995), Aly *et al.* (2004), Sarma (2004) and Rahman (2009) explored the day-of-the-week effect on the stock market returns. Kolahi (2006) and Camilleri (2008) investigated the turn-of-the-month effect in the market returns. Balaban and Bulu (1996) and Agathee (2010) studied the existence of semi-monthly stock market return effects. Kling and Gao (2005), Guo and Wang (2007), Sewraj *et al.* (2010), Sharma and Mahendru (2009), Nageswari and Selvam (2011), Pathak (2013), SiamiNamini *et al.* (2013), Kuria and Riro (2013) and Safeer and Kevin (2014) studied the presence of both the monthly as well as weekly effect in stock market. Silva (2010) and Darrat *et al.* (2013) researched the presence of month-of-the-year, day-of-the-week and turn-of-the-month effects in market returns. Garg *et al.* (2010), on the other hand studied all the four anomalies: Month-of-the-year, day-of-the-week, turn-of-the-month and mid-month effects in the secondary market returns.

The researchers have used regression model very extensively. French (1980), Balaban (1995), Aly *et al.* (2004), Kling and Gao (2005), Kolahi (2006), Camilleri (2008), Rahman (2009), Dash *et al.* (2011), Nyamosi (2011), Marrett and Worthington (2011), Debasish (2012), Li (2013), Ahsan and Sarkar (2013), Nageswari *et al.* (2013), Pathak (2013), SiamiNamini *et al.* (2013) and Kuria and Riro (2013) applied the Dummy Variable Regression Model. SiamiNamini *et al.* (2013) estimated the regression coefficients using three models: GARCH (1,1), GARCH-M and Modified GARCH. Camilleri (2008), Nageswari *et al.* (2013) and Pathak (2013) applied the Kruskal Walis Test in addition to the Dummy Variable Regression Model applied by them in their studies. Kling and Gao (2005), Nyamosi (2011), Marrett and Worthington (2011), Debasish (2012) and Kuria and Riro (2013) used Descriptive Statistics as an additional tool to the Regression Model. Another regression model used by the researchers is the Ordinary Least Squares (OLS) Regression Model.

Balaban and Bulu (1996), Sewraj *et al.* (2010), Agathee (2010), Sharma and Bodla (2011) and Chia and Liew (2012) used the OLS Model to carry out their research. Sewraj *et al.* (2010) made use of the GARCH and EGARCH Model along with the OLS model. Chia and Liew (2012) used the Threshold Generalized Autoregressive Conditional Hetroscedasticity (TGARCH) model along with the OLS Model. Pandey (2002) applied the Augmented Dickey-Fuller (ADF) test for unit roots and Augmented auto-regressive moving average model. Sarma (2004) and Nageswari and Selvam (2011) used the Kruskal Walis test to carry out their research on seasonal anomalies. Darrat *et al.* (2013), Stefanescu and Dumitriu (2013) applied the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach in order to arrive at their objectives.

Researchers also used the Descriptive Statistics approach to meet their objectives. Guo and Wang (2007) used statistical measurements such as mean, standard deviation, F-test, T-test and P-value (two-tailed) in their research. In the study by Garg *et al.* (2010), the significance of the difference between average returns was verified with the help of t-test. While Safeer and Kevin (2014) used only t-test, Silva (2010) used both t-test as well as Mann-Whitney Test to carry out the research.

The studies of French (1980), Balaban (1995), Pandey (2002), Sarma (2004), Kling and Gao (2005), Kolahi (2006), Guo and Wang (2007), Camilleri (2008), Rahman (2009), Dash *et al.* (2011), Nyamosi (2011), Marrett and Worthington (2011), Debasish (2012), Ahsan and Sarkar (2013), SiamiNamini *et al.* (2013), Kuria and Riro (2013) and Stefanescu and Dumitriu (2013) pointed towards the existence of anomalies in the stock market.

French (1980) found that the expected return to Monday was significantly lower than the expected return to other days of the week. Balaban (1995) and Sarma (2004) confirmed that highest volatility in stock market was observed on Monday and Friday had the lowest volatility. Pandey (2002) and Nyamosi (2011) found the presence of January effect for the stock returns in India and Kenya respectively. In their research, Kling and Gao (2005) revealed that average returns for March and April were higher compared to other months and Mondays were considerably weak and Fridays showed significantly positive average returns. Kolahi (2006) confirmed the existence of turn-of-the-month effect in European Stock Market. He found that days around the turn of the month (last and first three days of the month) exhibited higher rates of return than other days of the month. Guo and Wang (2007) found that among all the days of a week, Friday had the highest mean return. They also confirmed a positive March effect and a negative July effect. According to Camilleri (2008), pronounced end-of-month volatility may be attributable to a tendency for companies to issue announcements towards the end of the month. Rahman (2009) found a significant day-of-the-week effect in the Dhaka Stock Exchange. Dummy variable regression result showed that only Thursdays had positive and statistically significant coefficients. Dash *et al.* (2011) provided evidence for a month-of-the-year effect in Indian stock markets. They found positive November, August and December effects while a negative March effect. Marrett and Worthington (2011) concluded that market wide returns were significantly higher in April, July and December with evidence of small cap effect giving systematically higher returns in January, August and December. The study by Debasish (2012) found that all the eight selected Gas, Oil and Refineries companies evidenced month-of-the-year effect and mostly either on September, August or February. Only GAIL and HPCL evidenced significant October and July effect. Ahsan and Sarkar (2013) were struggling to find out January effect in Bangladesh. However, they found a significant positive return in June instead. SiamiNamini *et al.* (2013) confirmed the existence of January effect and Weekend effect. Wednesday's returns were significantly greater than Saturday's returns. In the study by Kuria and Riro (2013), they found that the coefficient of December month is statistically highly significant at 1 percent level of significance and that only Thursdays have positive and statistically significant coefficients. Stefanescu and Dumitriu (2013) studied the Month-of-the-year effects on Romanian capital market before and after the adhesion to European Union. According to them, changes occurred after the adhesion affected the Month-of-the-year effects for returns. Monthly seasonality of the returns passed from a positive January effect to negative May, September and November effects.

Balaban and Bulu (1996), Aly *et al.* (2004), Nageswari and Selvam (2011), Chia and Liew (2012), Li (2013) and Pathak (2013) did not find any anomaly in the stock market in their studies. According to Aly, Mehdian and Perry, Monday returns in the Egyptian stock market were positive and significant on average. However, Monday returns were not significantly different from returns of the rest of the week. Chia and Liew (2012) though observed significant positive returns in November, the prevalent January effect as documented in majority of the literature was not observed in this Japan stock market. In the study by Li (2013) results were not sufficient to confirm the existence of January effect in the small-cap firms.

Some researchers confirmed the existence of one anomaly; however, the other market anomalies were not confirmed in their studies. Such studies were conducted by Sewraj *et al.* (2010), Garg *et al.* (2010), Silva (2010), Darrat *et al.* (2013) and Safeer and Kevin (2014). Sewraj *et al.* (2010), though confirmed the existence of January effect, Monday effect was nonexistent in their study. Silva (2010) found no significant month-of-the-year effect or day-of-the-week effect. However, a significant turn-of-the-month effect was confirmed in their study. In the study by Darrat *et al.* (2013), the evidence strongly indicated the presence of robust Monday and Tuesday effects, whereby the returns on Monday and Tuesday were significantly lower than the return on the benchmark day of Wednesday in the Johannesburg Stock Exchange. A beginning-of-the-month effect was also quite pronounced in which second and third trading day returns were significantly larger than returns in other trading days. However, no compelling support was found for a monthly effect.

The above review of literature reveals that though a lot of research has been done concerning the anomalies in the stock markets in India, the research has been limited to only one stock index.

The current study therefore contributes to the literature additionally by studying the month-of-the-year effect across two indices of the most recognised stock exchange of India, National Stock Exchange (NSE). The indices are S and P CNX Nifty and S and P CNX Nifty Junior. Along with the indices, the study also covers top nine companies of both the indices. Hence, this will cast a more convincing shadow on the existence of monthly anomaly of stock returns in the Indian market.

MATERIALS AND METHODS

National Stock Exchange (NSE) is India's leading stock exchange and is responsible for the vast majority of share transactions. NSE has played a catalytic role in reforming the Indian securities market in terms of microstructure, market practices and trading volumes. Therefore, the paper takes NSE as a representative for Indian Stock Market. Two indices of NSE are taken in this study: S and P CNX Nifty and S and P CNX Nifty Junior. The S and P CNX Nifty is a well-diversified 50 stock index accurately reflecting overall market conditions. It is based upon solid economic research and is well respected internationally as a pioneering effort in better understanding how to make a stock market index. S and P CNX Nifty Junior (Junior Nifty), on the other hand, is an index comprised of the next rung of 50 most liquid stocks after S and P CNX Nifty. Stocks in junior nifty are filtered on their liquidity characterized by their impact cost and market value represented by their market capitalization. The stocks comprising S and P CNX Nifty and junior nifty are mutually exclusive i.e., a stock will never appear in both indexes at the same time. Along with these indices, the top nine companies (according to the market capitalisation) from both the indices are also taken in the study. From S and P CNX Nifty, the following companies are studied: Reliance Industries Limited, ITC, ONGC, Infosys, HDFC, Tata Motors, ICICI, Wipro and SBI. And from S and P CNX Nifty Junior, Dabur, Zee Entertainment, SAIL, Oracle Financial Services, Titan, GlaxoSmithkline Pharmaceuticals Limited, Container Corporation, Bank of India and Apollo Hospitals are taken for the purpose of this study. The daily closing levels of the representative indices and stocks for a period beginning on 1st April 2004 through 31th March 2013, representing the secondary data, are considered the reference period. This data has been taken from NSE’s website, Yahoo Finance and moneycontrol.com.

It is found from the extensive review of prior studies that most of the earlier studies on stock price behavior have used closing price for return generating procedure with an implied assumption of trading done at the closing price. The continuous compounded return is well accepted approach to measuring the daily returns. Therefore, the following equation is used to determine the continuous daily return of the stocks and indices for each working day:

$$R_t = \text{Ln}\ (p_t)\text{-Ln}\ (p_{t-1})$$

where, p_t is the price of the respective stock or index on day t, P_{t-1} is the prices of the respective stock or index on day t-1 and Ln (p_n) is the logarithm return of the respective stock or index on day n.

The reasons to choose logarithm returns over general returns are justified both theoretically and empirically. From the theoretically post of view, logarithmic returns are analytically more tractable when linked together with sub-period returns to form returns over longer intervals. Empirically, logarithmic returns are more likely to be normally distributed which is a prior condition of standard statistical techniques.

First, we analyzed the descriptive statistics of daily return of separate month, like mean, standard deviation and Coefficient of Variation (COV) to see which month has the highest or lowest mean return and the direction of the mean return of each month and also the relationship between the mean and the standard deviation of the daily return through COV.

The results of the regressions will be spurious if the dependent variable is non stationary. We therefore, determine whether the return of the series is stationary or not. One simple way of determining whether a series is stationary is to use a formal test of stationarity, that is, the Augmented Dickey-Fuller (ADF) test. The ADF test is a common method for determining unit roots. It consists of regressing the first difference of the series against a constant, the series lagged one period, the differenced series at n lag lengths and a time trend. The following equation has been used to test the stationarity of the series:

$$\Delta r_t = \alpha + \sum_{i=1}^{n} \beta_i \Delta r_{t-i} + \lambda t + \rho r_{t-1} + \varepsilon_t$$

If the coefficient of ρ is significantly different from zero, then the hypothesis that r is non stationary is rejected. The ADF test can be carried out with and without the constant and/or trend. One has also to choose the appropriate lag length. If a series is found to be non-stationary in level, one should difference the series until the stationarity is established.

At the stationary log series, the study performs the Dummy Variable Regression Model on the daily closing price returns which has been used in most of the previous studies as seen in the review of literature.

Dummy variables are "Proxy" variables or numeric stand-ins forqualitativefacts in aregression model. In regression analysis, thedependent variablesmay be influenced not only by quantitative variables (income, output, prices, etc.), but also by qualitative variables (gender, religion, geographic region, marital status etc.). Dummy-variable regressors can be used to incorporate these qualitative explanatory variables into a linear model, substantially expanding the range of application of regression analysis. Typically, these variables are used in the following applications: Time series analysis with seasonality or regime switching; analysis of qualitative data, such as survey responses; categorical representation and representation of value levels. Target domains may be economic forecasting, bio-medical research, credit scoring, response modeling and other fields. A dummyindependent variablewhich for some observation has a value of 0 will cause that variable'scoefficientto have no role in influencing thedependent variable while when the dummy takes on a value 1 its coefficient acts to alter the intercept. For example, suppose Gender is one of the qualitative variables relevant to a regression. Then, female and male would be the categories included under the Gender variable. If female is arbitrarily assigned the value of 1, then male would get the value 0. Then the intercept (the value of the dependent variable if all other explanatory variables hypothetically took on the value zero) would be the constant term for males but would be the constant term plus the coefficient of the gender dummy in the case of females.

In order to investigate the Monthly Effect in the return series, the following regression equation is used:

$$Y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t$$

where, y_t is the index return percent in the month t, ε_t is the error term (or the stochastic disturbance term) and The intercept term α_1 indicates mean return for the month of January.

Coefficients α_2.....α_{12} represent the average differences in return between January and each month. These coefficients should be equal to zero if the return for each month is the same and if there is no seasonal effect.

Ultimately, if the respective stocks and indices register January effect, its estimated co-efficient would be either (1) Higher than the returns of the other months of the year, or (2) Positive which may or may not be statistically significant.

RESULTS AND DISCUSION

The study first presents the descriptive statistics of daily return of separate month, like mean, standard deviation, to see which month has the highest or lowest mean return and the direction of the mean return of each month and also the relationship between the mean and the standard deviation of the daily return.

As can be seen, in Nifty, Reliance, HDFC, ICICI and SBI, highest mean return is reported in the month of September. And Infosys, Tata Motors and Wipro report the highest mean return in December. Though, neither Nifty nor any stock is gaining highest mean return in April; April and December are the only two months in which all the stocks and Nifty have positive returns. In the months of February and October, almost all the companies are showing negative mean returns (Table 1).

Across the companies in Nifty Junior, the highest and lowest mean returns are unevenly distributed. Where, Nifty Junior, Dabur and Oracle have highest mean returns in April; Zee Entertainment and Container have highest mean returns in July; and SAIL and Apollo have reported highest mean returns in the month of December. The lowest returns are mainly observed in the months of January, June and November. All the selected companies of Nifty Junior and the index itself have positive mean returns in the months July and December. And, in January and October, almost all the companies and the index have negative mean returns (Table 2).

Therefore, we see that both the indices and all the 18 stocks have reported positive mean returns in the month of December. And almost all the companies have negative mean returns in the month of October.

Standard Deviation measures the volatility and variability of a stock. It is a measure of the dispersion of a set of data from itsmean. It is evident from the above table that in the stocks across Nifty, the highest variability cannot be limited to a few months. However in the stocks of Nifty Junior, the market has been most active in the second quarter as in this quarter the stocks have shown highest variability. All the stocks and indices have shown lowest variability in the months of August, September and December. This means that the market has been least active in these three months (Table 3).

Table 1: Mean returns of nifty companies

Months	Nifty	Reliance	ITC	ONGC	Infosys	HDFC	Tata M	ICICI	Wipro	SBI
Jan	-0.0009	-0.0008	0.0005	0.0006	0.0000	-0.0004	-0.0004	0.0006	-0.0004	-0.0010
Feb	-0.0006	-0.0011	0.0001	-0.0058	0.0001	-0.0019	0.0002	-0.0029	-0.0015	-0.0018
Mar	0.0012	0.0014	0.0022	0.0019	0.0006	0.0009	0.0008	-0.0006	0.0020	-0.0013
Apr	0.0014	0.0029	0.0024	0.0008	0.0000	0.0022	0.0038	0.0026	0.0019	0.0023
May	-0.0005	-0.0003	-0.0013	-0.0010	0.0010	0.0006	-0.0041	-0.0005	0.0005	-0.0006
Jun	-0.0002	0.0002	0.0008	0.0004	0.0012	-0.0002	-0.0030	-0.0003	-0.0092	-0.0018
Jul	0.0015	0.0007	0.0026	0.0017	-0.0104	0.0023	0.0026	0.0027	-0.0004	0.0032
Aug	0.0002	0.0001	-0.0029	0.0004	0.0004	-0.0079	0.0011	-0.0009	-0.0030	-0.0004
Sep	0.0026	0.0032	0.0001	0.0015	0.0016	0.0045	-0.0059	0.0048	0.0002	0.0061
Oct	-0.0010	-0.0006	-0.0014	-0.0040	0.0012	-0.0012	-0.0039	-0.0012	-0.0004	-0.0024
Nov	0.0009	-0.0052	0.0024	0.0004	-0.0001	0.0021	0.0010	-0.0001	0.0019	0.0024
Dec	0.0016	0.0014	0.0004	0.0009	0.0017	0.0005	0.0046	0.0026	0.0026	0.0017

Table 2: Mean returns of nifty junior companies

Months	Nifty Jr.	Dabur	Zee	SAIL	Oracle	Titan	Glaxo	Container	BOI	Apollo
Jan	-0.0013	-0.0064	-0.0024	0.0004	-0.0004	-0.0008	-0.0016	-0.0006	-0.0005	0.0010
Feb	-0.0010	0.0020	-0.0036	-0.0005	0.0011	-0.0003	0.0032	-0.0007	-0.0019	0.0008
Mar	0.0005	0.0014	0.0024	0.0014	0.0001	0.0019	0.0000	0.0013	-0.0009	0.0019
Apr	0.0028	0.0025	0.0011	-0.0005	0.0034	0.0027	0.0018	-0.0028	0.0022	0.0007
May	-0.0002	0.0009	0.0029	0.0004	0.0013	0.0026	-0.0002	-0.0002	0.0003	0.0006
Jun	-0.0009	0.0002	0.0005	-0.0038	0.0028	-0.0018	-0.0002	-0.0003	-0.0024	0.0009
Jul	0.0020	0.0012	0.0033	0.0027	0.0004	0.0028	0.0003	0.0030	0.0033	0.0004
Aug	0.0005	0.0006	0.0007	0.0000	0.0009	0.0036	0.0006	0.0002	-0.0017	0.0007
Sep	0.0024	-0.0022	0.0020	0.0026	-0.0012	0.0018	0.0015	0.0013	0.0058	-0.0016
Oct	-0.0018	-0.0001	-0.0035	-0.0017	-0.0015	0.0021	-0.0009	-0.0012	-0.0018	-0.0004
Nov	0.0011	0.0010	-0.0039	-0.0024	-0.0020	0.0009	0.0012	-0.0012	0.0037	0.0017
Dec	0.0025	0.0023	0.0021	0.0044	0.0033	0.0017	0.0014	0.0026	0.0028	0.0019

Table 3: Standard deviation

Months	Nifty	Reliance	ITC	ONGC	Infosys	HDFC	Tata M	ICICI	Wipro	SBI
Jan	0.018	0.032	0.021	0.024	0.024	0.021	0.027	0.029	0.026	0.023
Feb	0.014	0.021	0.018	0.060	0.018	0.024	0.027	0.025	0.023	0.024
Mar	0.017	0.021	0.020	0.021	0.020	0.028	0.028	0.032	0.025	0.025
Apr	0.014	0.020	0.016	0.020	0.026	0.024	0.030	0.028	0.028	0.022
May	0.024	0.029	0.025	0.032	0.026	0.032	0.036	0.033	0.034	0.034
Jun	0.018	0.025	0.023	0.025	0.021	0.028	0.030	0.025	0.090	0.023
Jul	0.016	0.022	0.022	0.023	0.112	0.027	0.027	0.030	0.022	0.027
Aug	0.013	0.019	0.054	0.018	0.018	0.116	0.027	0.023	0.053	0.023
Sep	0.013	0.020	0.031	0.017	0.019	0.022	0.125	0.026	0.019	0.021
Oct	0.022	0.032	0.020	0.039	0.024	0.031	0.037	0.037	0.032	0.032
Nov	0.017	0.060	0.020	0.021	0.019	0.024	0.028	0.029	0.023	0.027
Dec	0.014	0.021	0.014	0.017	0.016	0.021	0.027	0.025	0.020	0.022
Months	Nifty Jr.	Dabur	Zee	SAIL	Oracle	Titan	Glaxo	Container	BOI	Apollo
Jan	0.022	0.069	0.036	0.038	0.032	0.029	0.016	0.021	0.034	0.027
Feb	0.015	0.018	0.037	0.030	0.028	0.035	0.015	0.019	0.031	0.024
Mar	0.019	0.018	0.028	0.035	0.024	0.032	0.018	0.017	0.034	0.018
Apr	0.015	0.021	0.030	0.029	0.027	0.027	0.016	0.055	0.031	0.019
May	0.026	0.027	0.031	0.042	0.033	0.034	0.023	0.029	0.039	0.030
Jun	0.022	0.030	0.029	0.034	0.031	0.055	0.018	0.026	0.033	0.021
Jul	0.018	0.022	0.029	0.033	0.025	0.027	0.014	0.020	0.034	0.017
Aug	0.014	0.018	0.023	0.026	0.023	0.027	0.017	0.017	0.026	0.016
Sep	0.014	0.055	0.025	0.024	0.021	0.022	0.014	0.017	0.024	0.060
Oct	0.022	0.027	0.032	0.039	0.033	0.041	0.017	0.025	0.041	0.025
Nov	0.016	0.026	0.058	0.031	0.027	0.027	0.018	0.019	0.029	0.025
Dec	0.015	0.017	0.031	0.030	0.027	0.029	0.016	0.016	0.029	0.027

COV is a statistical measure of the dispersion of data points in a data series around the mean. The standard deviation is the most common way to express variability but it's hard to interpret. COV makes interpretation easier. As can be seen from the above table, the highest variation of 810.49 is shown by SAIL in August, followed by 359.28 by GlaxoSmithkline in March, 277.29 by ITC in February, 262.16 by Oracle in March and 224.72 by Reliance in August. The lowest variation by -2003.72 is shown by Infosys in April, followed by

Table 4: Coefficient of variation

Months	Nifty	Reliance	ITC	ONGC	Infosys	HDFC	Tata M	ICICI	Wipro	SBI
Jan	-19.65	-39.22	39.87	37.72	-1247.51	-49.93	-75.58	49.69	-66.99	-24.24
Feb	-22.97	-18.91	277.29	-10.44	176.42	-12.40	147.75	-8.50	-14.95	-13.25
Mar	14.10	15.06	8.92	10.87	32.06	32.08	36.69	-55.78	12.46	-18.84
Apr	10.47	6.97	6.84	25.71	-2003.72	10.56	7.87	11.09	14.84	9.25
May	-49.37	-105.30	-19.77	-33.05	25.34	49.73	-8.81	-73.16	68.76	-60.51
Jun	-114.35	144.37	30.15	63.78	17.50	-139.61	-10.30	-72.70	-9.82	-13.15
Jul	10.74	32.12	8.25	13.29	-10.77	11.34	10.29	11.32	-61.12	8.34
Aug	81.84	224.72	-18.38	40.66	40.96	-14.63	23.67	-24.91	-17.80	-52.48
Sep	5.02	6.32	245.67	11.33	11.85	4.93	-21.21	5.53	82.42	3.37
Oct	-21.30	-55.93	-14.06	-9.69	19.11	-26.49	-9.45	-30.99	-84.92	-13.33
Nov	17.63	-11.46	8.35	49.39	-293.28	11.37	27.41	-311.16	11.87	11.44
Dec	8.45	15.27	33.58	18.91	9.20	45.69	5.97	9.56	7.70	12.69
Months	Nifty Jr.	Dabur	Zee	SAIL	Oracle	Titan	Glaxo	Container	BOI	Apollo
Jan	-16.34	-10.76	-15.10	96.99	-81.56	-38.25	-10.26	-33.29	-70.65	26.84
Feb	-15.00	9.02	-10.28	-57.01	25.71	-106.02	4.75	-26.68	-16.47	31.57
Mar	40.47	13.26	11.57	25.58	262.16	16.71	359.28	13.03	-36.29	9.61
Apr	5.39	8.46	26.68	-61.13	8.07	10.10	8.94	-20.03	14.22	25.89
May	-106.76	32.13	10.83	94.46	25.05	12.93	-132.46	-136.92	153.82	46.29
Jun	-24.32	157.87	56.24	-8.75	11.00	-30.19	-96.67	-88.05	-13.59	22.18
Jul	9.22	19.19	8.74	12.17	68.79	9.66	41.78	6.59	10.33	44.74
Aug	26.99	29.07	35.61	810.49	26.90	7.32	27.64	80.84	-15.24	23.07
Sep	5.91	-24.65	12.35	9.30	-17.11	12.71	9.27	13.54	4.18	-37.28
Oct	-12.25	-425.73	-9.12	-22.95	-21.54	19.35	-17.74	-21.51	-22.77	-59.50
Nov	14.55	25.47	-14.94	-13.06	-13.57	31.11	14.80	-15.16	7.68	14.88
Dec	5.93	7.71	15.06	6.87	8.10	17.36	11.07	6.17	10.57	14.17

-425.73 by Dabur in October, -311.96 by ICICI in November and -139.61 by HDFC in June. Thus, the COV is spread unevenly across months (Table 4).

Augmented dickey-fuller test for unit-root: The study proceeds to check the nature of the data as to whether it is stationary or not.

Figure 1 presents the combined graph of returns at Nifty and the selected companies under it; and Fig. 2 presents the combined graph of returns at Nifty Junior and the selected companies under it during the study period. It is indicated from the above figures that returns at both the indices and the selected 18 companies are stationary in nature.

The unit-root test is performed on the series in order to test the null hypothesis that the series has a unit root. The findings of the unit-root test and the Augmented Dickey- Fuller test are shown below in the following Table 5.

Decision rule: If resultant probability > level of significance ==> not reject null hypothesis
If resultant probability < level of significance ==> reject null hypothesis.

To test whether the series is stationary or not, we compare the resultant probability with our level of significance of 5% (assumed). Since across all the indices and stocks the calculated probability value of is less than 0.05, hence we reject our null hypothesis that is; the given index return or stock return has a unit root. Therefore, we conclude that the returns of both the indices and the given 18 companies are stationary in nature.

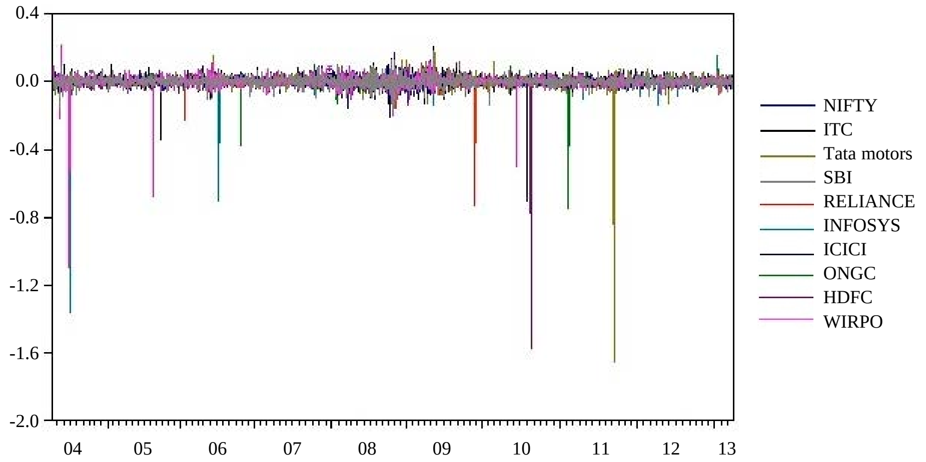

Fig. 1: Combined graphical returns for nifty companies

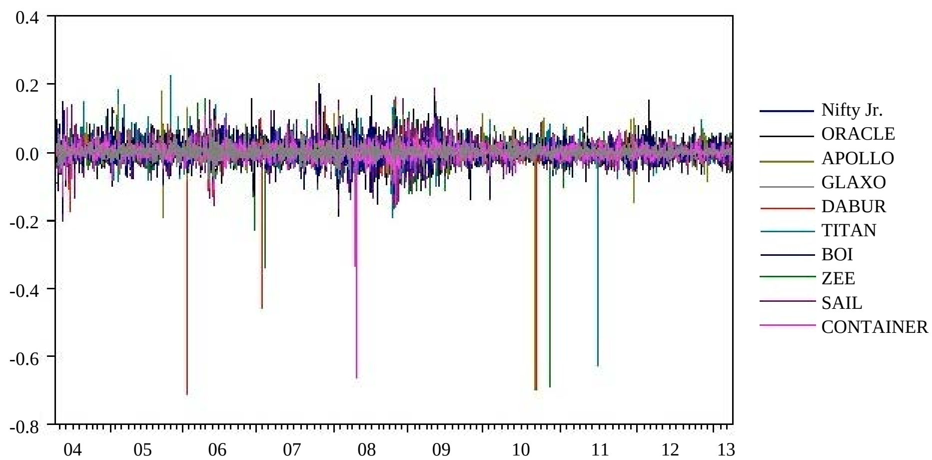

Fig. 2: Combined graphical returns for nifty junior companies

Table 5: Stationarity test

Company	Null hypothesis	Probability	Accept/Reject Ho	Result
Nifty	Nifty has a unit root	0.0001	Reject Ho	Series is stationary
Reliance	Reliance has a unit root	0.0001	Reject Ho	Series is stationary
ITC	ITC has a unit root	0.0001	Reject Ho	Series is stationary
ONGC	ONGC has a unit root	0.0001	Reject Ho	Series is stationary
Infosys	Infosys has a unit root	0.0001	Reject Ho	Series is stationary
HDFC	HDFC has a unit root	0.0001	Reject Ho	Series is stationary
Tata Motors	Tata Motors has a unit root	0.0001	Reject Ho	Series is stationary
ICICI	ICICI has a unit root	0.0000	Reject Ho	Series is stationary
Wipro	Wipro has a unit root	0.0001	Reject Ho	Series is stationary

Table 5: Countinue

Company	Null hypothesis	Probability	Accept/Reject Ho	Result
Nifty Jr.	Nifty Jr. has a unit root	0.0000	Reject Ho	Series is stationary
Dabur	Dabur has a unit root	0.0001	Reject Ho	Series is stationary
Zee	Zee has a unit root	0.0001	Reject Ho	Series is stationary
SAIL	SAIL has a unit root	0.0001	Reject Ho	Series is stationary
Oracle	Oracle has a unit root	0.0001	Reject Ho	Series is stationary
Titan	Titan has a unit root	0.0001	Reject Ho	Series is stationary
Glaxo	Glaxo has a unit root	0.0001	Reject Ho	Series is stationary
Container	Container has a unit root	0.0001	Reject Ho	Series is stationary
BOI	BOI has a unit root	0.0001	Reject Ho	Series is stationary
Apollo	Apollo has a unit root	0.0001	Reject Ho	Series is stationary

Table 6: Coefficients of regression

Months	Nifty	Reliance	ITC	ONGC	Infosys	HDFC	Tata M	ICICI	Wipro	SBI
Jan	0.472	0.704	0.782	0.764	0.995	0.891	0.916	0.783	0.893	0.614
Feb	0.874	0.926	0.865	0.035	0.977	0.739	0.912	0.247	0.781	0.751
Mar	0.243	0.459	0.535	0.672	0.873	0.769	0.816	0.701	0.549	0.897
Apr	0.213	0.232	0.504	0.965	0.999	0.557	0.402	0.524	0.584	0.231
May	0.811	0.858	0.501	0.593	0.798	0.808	0.435	0.728	0.827	0.884
Jun	0.672	0.742	0.928	0.933	0.768	0.958	0.586	0.757	0.028	0.763
Jul	0.169	0.618	0.439	0.711	0.01	0.525	0.531	0.482	0.996	0.114
Aug	0.545	0.765	0.198	0.946	0.912	0.086	0.755	0.613	0.513	0.845
Sep	0.048	0.186	0.881	0.775	0.69	0.266	0.251	0.165	0.879	0.008
Oct	0.944	0.936	0.477	0.128	0.759	0.866	0.463	0.558	0.999	0.595
Nov	0.302	0.146	0.492	0.946	0.991	0.566	0.773	0.823	0.571	0.217
Dec	0.153	0.465	0.97	0.926	0.673	0.839	0.301	0.494	0.463	0.309
Months	Nifty Jr.	Dabur	Zee	SAIL	Oracle	Titan	Glaxo	Container	BOI	Apollo
Jan	0.335	0.009	0.341	0.872	0.85	0.757	0.21	0.735	0.842	0.624
Feb	0.876	0.015	0.731	0.791	0.617	0.903	0.008	0.972	0.679	0.931
Mar	0.355	0.024	0.173	0.775	0.869	0.445	0.36	0.466	0.894	0.764
Apr	0.042	0.012	0.33	0.806	0.209	0.332	0.064	0.433	0.445	0.924
May	0.575	0.034	0.133	0.988	0.554	0.33	0.425	0.872	0.828	0.898
Jun	0.826	0.053	0.407	0.217	0.271	0.756	0.429	0.898	0.561	0.976
Jul	0.087	0.026	0.102	0.505	0.791	0.296	0.273	0.167	0.263	0.823
Aug	0.335	0.04	0.385	0.916	0.667	0.202	0.214	0.746	0.713	0.914
Sep	0.056	0.222	0.208	0.521	0.778	0.468	0.081	0.468	0.066	0.372
Oct	0.824	0.067	0.737	0.551	0.698	0.411	0.724	0.844	0.698	0.627
Nov	0.211	0.032	0.668	0.423	0.583	0.644	0.114	0.818	0.218	0.822
Dec	0.05	0.011	0.204	0.248	0.199	0.486	0.092	0.215	0.338	0.754

Dummy variable regression model: After the series were tested for stationarity, the Dummy Variable Regression Model was applied on the mean returns of each stock and index individually using SPSS. Each dummy variable took the value of one during the respective month and a value of zero otherwise. The Table 6 gives the coefficients of each month individually for every stock and index. We test our hypotheses at 90% confidence interval. If the calculated coefficient is less than 0.10, then the null hypothesis will be rejected. This means that the daily return for that particular month of the given stock or index will be statistically different from the daily returns of other months. In the above table, the shaded values are the ones in which the null hypothesis has been rejected. Thus, we see that Nifty and SBI have statistically significant returns in the month of September. ONGC has February returns as statistically significant. In Infosys, the daily returns of July are statistically deterrent from other months' returns. In HDFC, August; and in Wipro, June has statistically different returns from other months. In the Nifty Index, the stocks Reliance, ITC, Tata Motors and ICICI do not reveal any month in which there are any abnormal returns. In Nifty Junior index, there are 4 months whose daily return is statistically significant for the given period: April, June, September and December. Note that three of these four months represent the quarter end. Therefore, we may conclude that at the end of every quarter, Nifty generates statistically significant returns. Dabur gives statistically significant returns in every month except in the month of September. In Glaxo Smithkline Pharmaceuticals, again the returns for four months are statistically significant: February, April, September and December. Again like Nifty, three out of these four months represent quarter end and we can say that Glaxo Smithkline Pharmaceuticals generates statistically significant returns at the end of each quarter. The daily returns of Bank of India are statistically deterrent for September than the other months' returns. Under the Nifty Junior index, six out of nine selected companies do not show any statically significant returns for any month: Zee Entertainment, SAIL, Oracle, Titan, Container and Apollo.

CONCLUSION AND IMPLICATIONS

The focus of this study was on investigating the existence of month-of-the-year anomaly in stock returns in India. For this purpose, the daily closing prices of S and P CNX Nifty, S and P CNX Nifty Junior and 18 selected companies were taken for a period ranging from 1st April 2004 to 31st March 2013. The analysis of descriptive statistics showed that both the indices and all the 18 stocks have reported positive mean returns in the month of December. And almost all the companies have negative mean returns in the month of October. The regression results confirmed the seasonal effect in stock returns in India. The results of the study indicate that stock returns in India are not entirely random. Though, the much known 'January Effect' was not found in India, there were other months which confirmed the month-of-the-year anomaly in the Indian Stock Market. In many of the stocks, it was found that the return for the month at the end of any of the quarter (March, June, September, December) was significantly deterrent from that of other months' returns. However, these results are different from those seen in the review of literature which manly showed the presence of January Effect and December Effect in India. The reason behind these deterrent results can be difference in time periods taken for the study or because of the different stocks and indices studied.

The results of the study imply that the stock market in India is inefficient. The results have important practical implications to different capital market participants such as investors, managers and regulatory authorities. As a consequence, investors can formulate their investment strategies and timing on the basis of this result and can earn some abnormal return by predicting future prices.

Another implication of the study arises because the efficiency of the stock markets is closely related to the allocation of scarce capital resources. The allocation of capital resources to their most productive use can only be achieved in the presence of an efficient pricing mechanism which requires an efficient dissemination of the information. The presence of anomalies indicate, stock market inefficiency and therefore, SEBI as a regulator of India's stock market needs to take steps in order to increase the informational efficiency of the stock markets.

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