Stock Market Seasonality: A Study of the Indian Stock Market

Ash Narayan Sah
Assistant Professor
University of Petroleum & Energy Studies
Gurgaon 122 001(Haryana) India
Phone + 91 124 4540300
Fax +91 124 4540330
Mobile: +919891095235
Email:ashman24@rediffmail.com

1.0 Introduction

Seasonal variations in production and sales are a well known fact in business. Seasonality refers to regular and repetitive fluctuation in a time series which occurs periodically over a span of less than a year. The main cause of seasonal variations in time series data is the change in climate. For example, sales of woolen clothes generally increase in winter season. Besides this, customs and tradition also affect economic variables for instance sales of gold increase during marriage seasons. Similarly, stock returns exhibits systematic patterns at certain times of the day, week or month. The most common of these are monthly patterns; certain months provide better returns as compared to others i.e. the month of the year effect. Similarly, some days of the week provides lower returns as compared to other trading days i.e. days of the week effect.

The existence of seasonality in stock returns however violates an important hypothesis in finance that is efficient market hypothesis. The efficient market hypothesis is a central paradigm in finance. The EMH relates to how quickly and accurately the market reacts to new information. New data are constantly entering the market place via economic reports, company announcements, political statements, or public surveys. If the market is informationally efficient then security prices adjust rapidly and accurately to new information. According to this hypothesis, security prices reflect fully all the information that is available in the market. Since all the information is already incorporated in prices, a trader is not able to make any excess returns. Thus, EMH proposes that it is not possible to outperform the market through market timing or stock selection. However, in the context of financial markets and particularly in the case of equity market seasonal component have been recorded. They are called calendar anomalies (effects) in literature.

The presence of seasonality in stock returns violates the weak form of market efficiency because equity prices are no longer random and can be predicted based on past pattern. This facilitates market participants to devise trading strategy which could fetch abnormal profits on the basis of past pattern. For instance, if there are evidences of 'day of the week effect', investors may devise a trading strategy of selling securities on Fridays and buying on Mondays in order to make excess profits. Aggarwal and Tandon (1994) and Mills and Coutts (1995) pointed out that mean stock returns were unusually high on Fridays and low on Mondays. One of the explanation put forward for the existence of seasonality in stock returns is the 'tax-loss-selling hypothesis. In the USA, December is the tax month. Thus, the financial houses sell shares whose values have fallen to book losses to reduce their taxes. As of result of this selling, stock prices decline. However, as soon as the December ends, people start acquiring shares and as a result stock prices bounce back. This lead to higher returns in the beginning of the year, that is, January month. This is called 'January effect'. In India, March is the tax month, it would be interesting to find 'April Effect'.

2.0 Theoretical Background

The term 'efficient market' refers to a market that adjusts rapidly to new information. Fama (1970) stated , ' A market in which prices always fully reflect available information is called efficient.' If capital markets are efficient, investors cannot expect to achieve superior profits by adopting a certain trading strategy. This is popularly called as the efficient market hypothesis. The origins of the EMH can be traced back to Bachelier's doctoral thesis 'Theory of Speculation' in 1900 and seminal paper titled 'Proof That Properly Anticipated Prices Fluctuate Randomly' by Nobel Laureate Paul Samuelson in 1965. But it was Eugane Fama's work (1970) 'Efficient Capital Markets' who coined the term EMH and advocated that in efficient market securities prices fully reflect all the information.

It is important to note that efficiency here does not refer to the organisational or operational efficiency but informational efficiency of the market. Informational efficiency of the market takes three forms depending upon the information reflected by securities prices. First, EMH in its weak form states that all information impounded in the past price of a stock is fully reflected in current price of the stock. Therefore, information about recent or past trend in stock prices is of no use in forecasting future price. Clearly, it rules out the use of technical analysis in predicting future prices of securities. The semi-strong form takes the information set one step further and includes all publically available information. There is plethora of information of potential interest to investors. Besides past stock prices, such things as economic reports, brokerage firm recommendations, and investment advisory letters. However, the semi-strong form of the EMH states that current market prices reflect all publically available information. So, analysing annual reports or other published data with a view to make profit in excess is not possible because market prices had already adjusted to any good or bad news contained in such reports as soon as they were revealed. The EMH in its strong form states that current market price reflect all –both public and private information and even insiders would find it impossible to earn abnormal returns in the stock market. However, there is the notion that some stocks are priced more efficiently than others which is enshrined in the concept of *semi-efficient market hypothesis*. Thus, practitioners support the thesis that the market has several tiers or that a pecking order exist. The first tier contains well-known stocks such as Reliance Industries and Sail which are priced more efficiently than other lesser-known stocks such as UCO Bank. However, instead of considering stocks, we analyzed this phenomenon using Nifty Junior index which is an index of next most liquid stocks after S&P Nifty.

3.0 Review of Literature

Seasonality or calendar anomalies such as month of the year and day of the week effects has remained a topic of interest for research since long time in developed as well as developing countries. Watchel (1942) reported seasonality in stock returns for the first time. Rozeff and Kinney (1976) documented the January effect in New York Exchange stocks for the period 1904 to 1974. They found that average return for the month of January was higher than other months implying pattern in stock returns. Keim (1983) along with seasonality also studied size effects in stock returns. He found that returns of small firms were significantly higher than large firms in

January month and attributed this finding to tax-loss-selling and information hypothesis. A similar conclusion was found by Reinganum (1983), however, he was of the view that the entire seasonality in stock returns cannot be explained by tax-loss-selling hypothesis. Gultekin and Gultekin (1983) examined the presence of stock market seasonality in sixteen industrial countries. Their evidence shows strong seasonalities in the stock market due to January returns, which is exceptionally large in fifteen of sixteen countries. Brown et al. (1985) studied the Australian stock market seasonality and found the evidence of December-January and July-August seasonal effects, with the latter due to a June-July tax year. However, Raj and Thurston (1994) found that the January and April effects are not statistically significant in the NZ stock market. Mill and Coutts (1995) studied calendar effect in FTSE 100, Mid 250 and 350 indices for the period 1986 and 1992. They found calendar effect in FTSE 100. Ramcharan (1997), however, didn't find seasonal effect in stock retruns of Jamaica. Choudhary (2001) reported January effect on the UK and US returns but not in German returns. Fountas and Segredakis (2002) studied 18 markets and reported seasonal patterns in returns. The reasons for the January effect in stock returns in most of the developed countries such as US, and UK attributed to the tax loss selling hypothesis, settlement procedures, insider trading information. Another effect is window dressing which is related to institutional trading. To avoid reporting to many losers in their portfolios at the end of year, institutional investors tend to sell losers in Decembers. They buy these stocks after the reporting date in January to hold their desired portfolio structure again.

Researchers have also reported half- month effect in literature. Various studies have reported that daily stock returns in first half of month are relatively higher than last half of the month. Ariel (1987) conducted a study using US market indices from 1963 to 1981 to show this effect. Aggarwal and Tandon (1994) found in their study such effect in other international markets. Ziemba (1991) found that returns were consistently higher on first and last four days of the month.

The holiday effect refers to higher returns around holidays, mainly in the pre-holiday period as compared to returns of the normal trading days. Lakonishok and Smidt (1988) studied Dow Jones Industrial Average and reported that half of the positive returns occur during the 10 pre-holiday trading days in each year. Ariel (1990) showed using US stock market that more than one-third positive returns each year registered in the 8 trading days prior to a market-closed holiday. Similar conclusion were brought by Cadsby and Ratner (1992) which documented significant pre-holiday effects for a number of stock markets. However, he didn't find such effect in the European stock markets. Husain (1998) studied Ramadhan effect in Pakistan stock market. He found significant decline in stock returns volatility in this month although the mean return indicates no significant change.

There are also evidences of day of the week effect in stock market returns. The Monday effect was identified as early as the 1920s. Kelly (1930) based on three years data of the US market found Monday to be the worse day to buy stocks. Hirsch (1968) reported negative returns in his study. Cross (1973) found the mean returns of the S&P 500 for the period 1953 and 1970 on Friday was higher than mean return on Monday. Gibbons and Hess (1981) also studied the day of the week effect in US stock returns of S&P 500 and CRSP indices using a sample from 1962 to 1978. Gibbons and Hess reported negative returns on Monday and higher returns on Friday. Smirlock and Starks (1986) reported similar results. Jaffe and Westerfield (1989) studied day of the week effect on four international stock markets viz. U.K., Japan, Canada and Australia. They found that lowest returns occurred on Monday in the UK and Canada. However, in Japanese and Australian market, they found lowest return occurred on Tuesday. Brooks and Persand (2001) studied the five southeast Asian stock markets namely Taiwan, South Korea, The Philippines, Malaysia and Thailand. The sample period was from 1989 to 1996. They found that neither South Korea nor the Philippines has significant calendar effects. However, Malaysia and Thailand showed significant positive return on Monday and significant negative return on Tuesday. Ajayi& al. (2004) examined eleven major stock market indices on Eastern Europe using data from 1990 to 2002. They found negative return on Monday in six stock markets and positive return on Monday in rest of them. Pandey (2002) reported the existence of seasonal effect in monthly stock returns of BSE Sensex in India and confirmed the January effect. Bodla and Jindal (2006) studied Indian and US market and found evidence of seasonality. Kumari and Mahendra (2006) studied the day of the week effect using data from 1979 to 1998 on BSE and NSE. They reported negative returns on Tuesday in the Indian stock market. Moreover, they found returns on Monday were higher compared to the returns of other days in BSE and NSE. Choudhary and Choudhary (2008) studied 20 stock markets of the world using parametric as well as non-parametric tests. He reported that out of twenty, eighteen markets showed significant positive return on various day other than Monday. The scope of the study is restricted to days-of-the week effect, weekend effect and monthly effect in stock returns of S&P CNX Nifty and select firms. The half month effect and holiday effect are not studied here.

4.0 Objective

The objective of the study are as follows:

a) To examine days of the week effect in the returns of S&P CNX Nifty
b) To examine weekend effect in S&P CNX Nifty returns.
c) To examine the seasonality in monthly returns of the BSE Sensex.

5.0 Hypotheses

a) Our first hypothesis is that returns on all the days of weeks are equal. Symbolically,

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4$$

$$H_1 : at\ least\ one\ \beta_i\ is\ different$$

b) Our second hypothesis is as follows:

$$H_0 : \beta_1 = 0$$

$$H_1 : \beta_1 \neq 0$$

c) Our third hypothesis is:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11}$$

$$H_1 : at\ least\ one\ \beta\ is\ different$$

6.0 Data and its Sources

The monthly data on S&P Nifty for the period April 1997 to March 2009 obtained from the Handbook of Statistics on Indian Economy published by the Reserve Bank of India. We also collected daily data on S&P Nifty from 1st January 2005 to 31st December 2008 from www. nseindia.com for studying the above objectives.

7.0 Research Methodology

To examine the stock market seasonality in India, first we measure stock return of Nifty as given below:

$$R_t = (\ln P_t - \ln P_{t-1}) * 100 \tag{1}$$

where R_t is the return in period t, P_t and P_{t-1} are the monthly (daily) closing prices of the Nifty at time t and t-1 respectively. It is also important to test stationarity of a series lest OLS regression results will be spurious. Therefore, we will first test whether Nifty return is stationary by AR(1) model. We also use DF and ADF tests which are considered more formal tests of stationarity.

For testing stationarity, let us consider an AR(1) model

$$y_t = \rho_1 y_{t-1} + e_t \tag{2}$$

The simple AR(1) model represented in equation (2) is called a *random walk model*. In this AR(1) model if $|\rho_1| < 1$, then the series is I(0) i.e. stationary in level, but if $\rho_1 = 1$ then there exist what is called unit root problem. In other words, series is non-stationary. Most economists think that differencing is warranted if estimated $\rho > 0.9$; some would difference when estimated $\rho > 0.8$. Besides this, there are some formal ways of testing for stationarity of a series. .

Dickey-Fuller test involve estimating regression equation and carrying out the hypothesis test The simplest approach to testing for a unit root is with an AR(1) model:. Let us consider an AR(1) process:

$$y_t = c + \rho y_{t-1} + \varepsilon_t \tag{3}$$

where c and ρ are parameters and is assumed to be white noise. If $-1 \prec \rho \prec 1$, then y is a stationary series while if $\rho = 1$, y is a non-stationary series. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series is involves whether the absolute value of ρ is strictly less than one. The test is carried out by estimating an equation with y_{t-1} subtracted from both sides of the equation:

$$\Delta y_t = c + \gamma y_{t-1} + \varepsilon_t \tag{4}$$

where $\gamma = \rho - 1$, and the null and alternative hypotheses are

$$H_0 : \gamma = 0$$
$$H_1 : \gamma \prec 0$$

The DF test is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances is violated. The ADF controls for higher-order correlation by adding lagged difference terms of the dependent variable to the right-hand side of the regression:

$$\Delta y_t = c + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + ... + \delta_p \Delta y_{t-p} + \varepsilon_t \qquad (5)$$

This augmented specification is then tested for

$$H_0 : \gamma = 0$$
$$H_1 : \gamma \prec 0$$

in this regression.

Next, to test the presence of seasonality in stock returns of Nifty, we have used one technique called dummy variable regression model. This technique is used to quantity qualitative aspects such as race, gender, religion and after that one can include as an another explanatory variable in the regression model. The variable which takes only two values is called dummy variable. They are also called categorical, indicator or binary variables in literature. While 1 indicates the presence of an attribute and 0 indicates absence of an attribute. There are mainly two types of model namely ANOVA and ANCOVA.

This study uses ANOVA model. Analysis of variance (ANOVA) model is that model where the dependent variable is quantitative in nature and all the independent variables are categorical in nature. To examine the weekend effect and days of the week effect, the following dummy variable regression model is specified as follows:

$$Nifty\ \ returns = \alpha + \beta_1 Monday + \beta_2 Tuesday + \beta_3 wednesday + \beta_4 thrusday + \mu \qquad (6)$$

The variables Monday, Tuesday, Wednesday and Thursday are defined as:

Monday = 1 if trading day is Monday; 0 otherwise

Tuesday = 1 if trading day is Tuesday; 0 otherwise,

Wednesday = 1 if the trading day is Wednesday; 0 otherwise

Thursday = 1 if the trading day is Thursday; 0 otherwise

α represents the return of the benchmark category which is Friday in our study. Similarly, to find whether there are monthly effects in Nifty returns, we used ANOVA model specified below as:

$$Nifty\ \ returns = \alpha + \beta_1 D_{June} + \beta_2 D_{July} + \beta_3 D_{Aug} + \beta_4 D_{sep} + \beta_5 D_{Oct} + \beta_6 D_{Nov} + \beta_7 D_{Dec} + \beta_8 D_{Jan} + \beta_9 D_{Feb} + \beta_{10} D_{Mar} + \beta_{11} D_{April} + \mu \tag{7}$$

where Y = Monthly returns of Nifty

D_1= 1 if the month is June; 0 otherwise

D_2 = 1 if the month is July; 0 otherwise

D_3 = 1 if the month is August; 0 otherwise

D_4 = 1 if the month is September; 0 otherwise

D_5 = 1 if the month is October; 0 otherwise

D_6 = 1 if the month is November; 0 otherwise

D_7 = 1 if the month is December; 0 otherwise

D_8 = 1if the month is January; 0 otherwise

D_9 = 1 if the month is February; 0 otherwise

D_{10} = 1 if the month is March; 0 otherwise

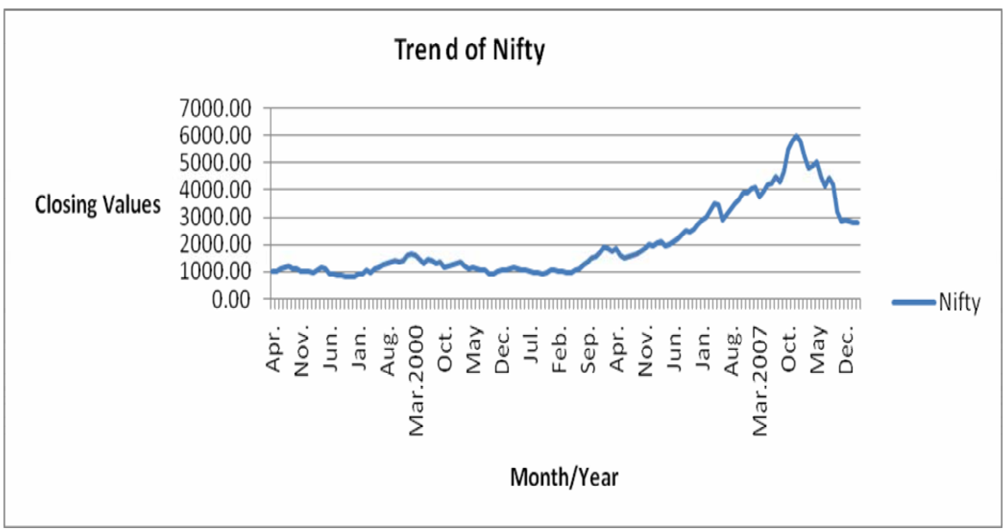
D_{11} = 1 if the month is April; 0 otherwise

α represents the mean return on the May month where as β_1 to β_{11} indicate the shift in mean returns across months. Statistically significant values of β's imply significant shifts in mean monthly returns, thus confirming the existence of the month of the year effect. The problem with this approach is that disturbance error term may have autocorrelation. Besides this, residual may contain ARCH effect. Therefore, we will test autocorrelation and ARCH effect in residual and improve our (6) and (7) model accordingly.

8.0 Results

At the outset, we plotted the trend of S&P CNX Nifty in Fig.1 which shows the movement of index over the sample period. For a long time hovering between 1000 and 2000, Nifty crossed the 2000 mark November 2005. Since then the one can see rising trend in Nifty till September 2008. After September 2008, we witnessed a stock market crash in the backdrop of mortgage crisis in the US followed by economic slowdown round the world which is quite visible in the movement of Nifty also.

Fig. 1



Next, we computed descriptive statistics of returns of Nifty and Junior Nifty. The results are reported in Table 1 which show the mean returns of Nifty and Junior Nifty for the period April 1997 and March 2009 are 0.93 and 1.38 percent respectively. Junior Nifty provided higher mean return than the Nifty over the sample period. As the Nifty and Junior Nifty returns are not normally distributed evident from coefficient of skewness and kurtosis, one can use median return instead of mean to represent returns of Nifty and Junior Nifty which are 1.58 and 2.38

percent respectively. Thus, it is clear that Junior Nifty yielded better returns over the sample period.

Table 1: Descriptive Statistics (%)

Summary Statistics	Nifty	Junior Nifty
Mean	0.93	1.38
Median	1.58	2.38
Standard Deviation	6.71	9.75
Minimum	-23.71	-27.66
Maximum	17.01	32.09
Skewness	-0.6029	-0.44
Kurtosis	0.5049	0.97

The variability in returns as measured by standard deviation which is the square root of variance The standard deviation is a conventional measure of volatility. Volatility as measured by standard deviations of returns of the sample period for Nifty and Junior Nifty are 6.71 and 9.75 percent respectively. Thus, it is evident that Junior Nifty is more volatile than the Nifty implying investment in Junior Nifty is more riskier.

Table 2: AR(1) Model

Monthly Series	
Level Series	Return Series
$Nifty_t = 35.0224 + 0.989\,Nifty_{t-1}$ (1.21) (83.725)	$Nifty_t = 0.58 + 0.2686\,Nifty_{t-1}$ (0.9) (3.29)
$NJunior_t = 35.0224 + 0.989\ NJunior_{t-1}$ (1.21) (83.725)	$NJunior_t = 35.0224 + 0.989\ NJunior_{t-1}$ (0.74) (4.11)
Daily Series	
Level Series	Return Series
$Nifty_t = 11.87 + 0.9969\,Nifty_{t-1}$ (1.46) (466.11)	$Nifty_t = 0.79 + 0.07\,Nifty_{t-1}$ (0.33) (2.25)
$NJunior_t = 20.01 + 0.997\ NJunior_{t-1}$ (1.17) (409.28)	$NJunior_t = 0.0154 + 0.1624\ NJunior_{t-1}$ (0.00) (5.18)

In time series econometrics, it is now customary to check stationarity of a series before using it in regression analysis in order to avoid spurious regression.

We tested the stationarity of Nifty, Junior Nifty by AR(1) model and augmented Dickey-Fuller Test; while the former is an informal test, the later is a formal test of stationarity. The results of AR(1) model and ADF are reported in Table 2 and Table 3. The results of AR(1) model show that monthly and daily Nifty and Nifty Junior series are not stationary in their level form. However, AR(1) model fitted to Nifty and Nifty Junior return series are stationary.

Table 3: Results of ADF Test

Series	Original Series	Return Series
Monthly Nifty	-1.1851	-4.59*
Monthly Junior Nifty	-1.564	-4.2
Daily Nifty	-1.48	-15.15
Daily Junior Nifty	-1.32	-15.46

* MacKinnon critical values for rejection of hypothesis of a unit root at 1%, 5% and 10% are -3.4786, -2.8824 and -2.5778 respectively.

The results of augmented Dickey-Fuller test is very much in consistent with AR(1) model. Table 3 shows that both monthly and daily Nifty and Nifty Junior are non-stationary in their level form. However, return series of Nifty and Nifty Junior are stationary as the null of unit root can be rejected at conventional level of 1%, 5% and 10%. Thus, analysis of stock market seasonality is based on return series of Nifty and Nifty Junior as they are stationary.

Next, we estimated model (6) to study days of the week effects in daily Nifty and Nifty Junior returns. The results for Nifty are reported in Table 4. The benchmark day in the model is Friday represented by the intercept which provided a return of 0.08 percent on an average of the sample period.

Table 4. Results of Equation (6) for Nifty

Variables	Coefficients	t-statistic	P-Value
Intercept	0.0836	0.624	0.53
Monday	-0.0875	-0.46	0.64
Tuesday	-0.0405	-0.21	0.83
Wednesday	-0.0432	-0.22	0.82
Thursday	-0.0784	-0.41	0.68
R^2 =0.0002 F Statistic = 0.06(0.99) Ljung-Box Q(2) = 0.7045 (0.40)			
D-W Statistic = 1.86 ARCH LM Test(1): F- stat = 54.31 (0.00)			
Note: Figures in () are p-values			

Returns of Monday, Tuesday, Wednesday and Thursday can be found out by deducting the coefficients of these days from the benchmark day, that is, Friday which were 0.1711, 0.1241, 0.1268 and 0.162 respectively. The coefficient of Monday is not significant at 5 percent level which indicates that there is no *weekend effect* in Nifty returns. Further, none of the coefficients are significant at conventional levels of significance indicating that there is no days of the week effects in the Nifty returns. R^2 is 0.0002 which is very low, and F-statistic indicates that the overall fit of the model is poor. Further, Durban-Watson statistic of 1.86 indicates autocorrelation in the residuals. The Ljung-Box Q statistic for the hypothesis that there is no serial correlation upto order of 2 is 0.7045 with an insignificant p-value of 0.40 which indicates that we have autocorrelation problem of order one. However, return series exhibits autoregressive conditional heteroskedasticity (ARCH) effects. We corrected the results for autocorrelation of order one by including an AR(1) term on the right hand side of the dummy regression model and ARCH effect is taken care of by fitting a benchmark GARCH (1,1) model.

Table 5: Results of Equation (6) for Nifty corrected for autocorrelation and ARCH Effect

Mean Equation			
Variables	Coefficients	t-statistic	P-Value
Intercept	0.2368	2.53	0.01
Monday	-0.0838	-0.72	0.46
Tuesday	-0.1362	-1.018	0.30
Wednesday	-0.0912	-0.70	0.47
Thursday	-0.0164	-0.13	0.89
AR(1)	0.0767	2.03	0.04
Variance Equation			
C	0.09	4.94	0.00
ARCH(1)	0.1674	8.45	0.00
GARCH(1)	0.8086	40.53	0.00
Ljung –Box Q (5) = 5.33 (0.25) ARCH LM Test(1): F- stat = 0.1645(0.68)			

Table 5 shows that after correcting for serial autocorrelation and ARCH effect, we found *Friday effect* in Nifty returns. However, our analysis do not find weekend effect. The Ljung-Box Q statistic shows that there is no pattern in residual. ARCH LM test also indicate that there is no ARCH effect in residual now.

We also examined the presence of seasonality in Nifty Junior. The results are given in Table 6 which shows that there is neither weekend effect or days of the week effects in Nifty Junior.

Table 6. Results of Equation (6) for Nifty Junior

Variables	Coefficients	t-statistic	P-Value
Intercept	0.1824	1.20	0.22
Monday	-0.2988	-1.40	0.16
Tuesday	-0.0766	-0.35	0.72
Wednesday	-0.2191	-1.024	0.30
Thursday	-0.3149	-1.46	0.14

R^2 =0.003 F Statistic = 0.84 (0.49) Ljung-Box Q(5) = 26.55 (0.00)
D-W Statistic = 1.70 ARCH LM Test(1): F- stat = 145.54 (0.00)
Note: Figures in () are p-values.

The coefficient of Monday is not significant at 5 percent level which indicates that there is no *weekend effect* in Nifty Junior returns. None of the coefficients are significant at conventional levels of significance implying that there are no days of the week effects in the Nifty Junior returns. R^2 is 0.003 which is very low, and F-statistic indicates that the overall fit of the model is poor. Further, Durban-Watson statistic of 1.7 indicates autocorrelation in the residuals. The Ljung-Box Q statistic for the hypothesis that there is no serial correlation upto order of 5 is 26.55 with a significant p-value of 0.00 which indicates that we have autocorrelation problem of higher order. Nifty Junior series also exhibits autoregressive conditional heteroskedasticity (ARCH) effects. We corrected the results for autocorrelation of order one by including an AR(1) term on the right hand side of the dummy regression model and ARCH effect is taken care of by fitting a benchmark GARCH (1,1) model.

Autoregressive conditional heteroskedasticity (ARCH) model was first introduced by Engle (1982), which does not assume variance of error to be constant. In ARCH\GARCH models, the conditional mean equation is specified, in the baseline scenario, by an AR(p) process i.e. is regressed on its own past values. Let the conditional mean under the ARCH model may be represented as:

$$y_t = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \beta_n x_n + \mu_t \text{ and } \mu_t \sim (N, 0, \sigma_t^2) \quad (8)$$

In equation (8), the dependent variable y_t varies over time. Similarly, conditional variance of μ_t may be denoted as σ_t^2, which can be represented as:

$$\sigma_t^2 = \text{var}(u_t \mid u_{t-1}, u_{t-2}.....) = E[(u_t - E(u_t)^2 \mid u_{t-1}, u_{t-2}....)]$$

It is usually assumed that $E(\mu_t) = 0$, so:

$$\sigma_t^2 = \text{var}(u_t \mid u_{t-1}, u_{t-2}....) = E(u_t^2 \mid u_{t-1}, u_{t-2}, ...) \quad (9)$$

Equation (9) states that the conditional variance of a zero mean is normally distributed random variable u_t is equal to the conditional expected value of the square of u_t. In ARCH model, 'autocorrelation in volatility' is modeled by allowing the conditional variance of the error term, σ_t^2, to depend immediately previous value of the squared error. This may be represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (10)$$

The above model is ARCH (1) where, the conditional variance is regressed on constant and lagged values of the squared error term obtained from the mean equation. In equation (5.12), conditional variance must be strictly positive. To ensure that these always result in positive conditional variance, all coefficients in the conditional variance are usually required to be non-negative. In other words, this model make sense if $\alpha_0 > 0$ and $\alpha_1 \geq 0$. However, if $\alpha_1 = 0$, there are no dynamics in the variance equation. An ARCH (p) can be specified as:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + ... + \alpha_p \varepsilon_{t-p}^2 \qquad (11)$$

This ARCH model might call for a long-lag structure to model the underlying volatility. A more parsimonious model was developed by Bollerslev (1986) leading to generalized ARCH class of models called GARCH in which, the conditional variance depends not only on the squared residuals of the mean equation but also on its own past values. The simplest GARCH (1, 1) is:

$$\sigma^2_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma^2_{t-1} \qquad (12)$$

The conditional volatility as defined in the above equation is determined by three effects namely, the intercept term given by w, the ARCH term expressed by $\alpha_1 \varepsilon_{t-1}^2$ and the forecasted volatility from the previous period called GARCH component expressed by $\beta_1 \sigma_{t-1}^2$. Parameters w and α should be higher than 0 and β should be positive in order to ensure conditional variance σ^2 to be nonnegative. Besides this, it is necessary that $\alpha_1 + \beta_1 \prec 1$. This condition secures covariance stationarity of the conditional variance. A straightforward interpretation of the estimated coefficients in (12) is that the constant term ω is the long-term average volatility, i.e. conditional variance, whereas α and β represent how volatility is affected by current and past information, respectively.

Table 7: Results of Equation (6) for Nifty Junior corrected for autocorrelation and ARCH Effect

Mean Equation			
Variables	Coefficients	t-statistic	P-Value
Intercept	0.3572	3.74	0.001
Monday	-0.2962	-2.47	0.01
Tuesday	-0.2183	-1.53	0.12
Wednesday	-0.2849	-2.1	0.03
Thursday	-0.1672	-1.27	0.2
AR(1)	0.1667	4.74	0.00
Variance Equation			
C	0.1387	4.78	0.00
ARCH(1)	0.1833	9.41	0.00
GARCH(1)	0.789	41.99	0.00
F-stat = 2.28 (0.02) Ljung –Box Q (5) =7.12(0.12)			
ARCH LM Test(1): F- stat = 1.37 (0.24)			

Table 7 shows that after correcting for serial autocorrelation and ARCH effect, we found *weekend effect* in Nifty Junior returns. Our study also found significant seasonality in Nifty Junior returns across the days. Returns of Monday, Wednesday and Friday are significantly different from each other. The F-statistic shows that at least one beta coefficient is different from zero. The Ljung-Box Q statistic shows that there is no pattern in residual. ARCH LM test also indicate that there is no ARCH effect in residual now.

We also examined seasonality of Nifty and Nifty Junior return using monthly data. We estimated equation (7). The results for Nifty are reported in Table 8. The benchmark month in the model is May represented by the intercept which provided negative return of -0.7132 percent on an average over the sample period. None of the coefficients are significant except December month which indicate the presence of December effect in Nifty monthly returns.

Table 8: Results of Equation (7) for Nifty

Variables	Coefficients	t-statistic	P-Value
Intercept	-0.7132	-0.35	0.71
June	-0.8535	-0.30	0.76
July	3.1781	1.13	0.25
August	1.5309	0.54	0.58
September	2.1704	0.77	0.44
October	-0.2136	-0.07	0.93
November	1.8055	0.64	0.52
December	5.047	1.79	0.07
January	3.4969	1.24	0.21
February	1.1607	0.41	0.67
March	-0.2425	-0.08	0.93
April	-0.2809	-0.09	0.92
R^2 =0.06 F Statistic = 0.84(0.59) Ljung-Box Q(5) = 11.85(0.03)			
D-W Statistic = 1.46 ARCH LM Test(1): F- stat = 0.8851 (0.34)			
Note: Figures in () are p-values			

R^2 is 0.06 which is very low, and F-statistic indicates that the overall fit of the model is poor. Further, Durban-Watson statistic of 1.46 indicates autocorrelation in the residuals. The Ljung-Box Q statistic for the hypothesis that there is no serial correlation up to order of 5 is 11.85 with a significant p-value of 0.03 which indicates that we have autocorrelation problem of higher order. However, monthly Nifty returns do not exhibits autoregressive conditional heteroskedasticity (ARCH) effects. Therefore, we augmented the model specified in equation (7) with autoregressive order of 5 and moving average order of 1 and 5 on a trial and error basis. The results are reported in Table 9 which shows the presence of seasonality in monthly returns of Nifty. The coefficients of July, September and January are statistically significant at 5 percent level. The coefficient of December month is statistically highly significant at 1 percent level of significance. The augmented model has R-square of 0.22 which shows that 22 percent of the variations are explained by these months. F-statistic is 2.62 with significant p-value of 0.002 implying that the null of all slope coefficients is rejected at 1 percent level of significance.

Table 9: Results of Equation (7) for Nifty

Variables	Coefficients	t-statistic	P-Value
Intercept	-1.6045	-1.03	0.30
June	-0.13	-0.06	0.94
July	4.3899	1.97	0.05
August	2.2566	0.91	0.36
September	3.9858	1.86	0.06
October	-0.0504	-0.02	0.98
November	3.1714	1.54	0.12
December	5.8317	2.52	0.01
January	4.8644	2.08	0.03
February	2.5038	1.07	0.28
March	0.1636	0.07	0.94
April	0.7953	0.39	0.69
AR(5)	0.6094	6.77	0.00
MA(1)	0.3559	453.72	0.00
MA(5)	0.689	-9.89	0.00
R^2 =0.22 F Statistic = 2.62(0.002) Ljung-Box Q(5) = 1.73 (0.42)			
D-W Statistic = 1.96			
Note: Figures in () are p-values			

Ljung –Box Q statistic of augmented model of order up to 5 is 1.73 with insignificant p value of 0.42 which implies that there is no pattern left in residual. This is also evident from D-W statistics of 1.96 which is very close to 2.

Table 10: Results of Equation (7) for Nifty Junior

Variables	Coefficients	t-statistic	P-Value
Intercept	-0.0106	-0.0037	0.99
June	-3.1408	-0.79	0.42
July	2.5269	0.63	0.52
August	2.78	0.70	0.48
September	1.6919	0.42	0.67
October	-2.1813	-0.55	0.58
November	1.6522	0.41	0.67
December	7.2491	1.82	0.06
January	4.0079	1.01	0.31
February	0.131	0.03	0.97
March	-3.3807	-0.85	0.39
April	-0.3954	-0.09	0.92
R^2 =0.09 F Statistic = 1.20(0.28) Ljung-Box Q(5) = 19.31(0.00)			
D-W Statistic = 1.33 ARCH LM Test(1): F- stat = 12.36 (0.00)			
Note: Figures in () are p-values			

Finally, we examined the seasonality of monthly Nifty Junior returns. We estimated the model specified in equation (7) for Nifty Junior. The results are reported in Table 10 which shows that December effect is present in Nifty Junior returns. Besides this, the coefficient of June month is found to be statistically significant at 5 percent level indicating the presence of seasonality in the returns of Nifty Junior. In this regression model, R^2 is 0.09 which is very low, and F-statistic indicates that the overall fit of the model is poor. Further, Durban-Watson statistic of 1.33 indicates autocorrelation in the residuals. The Ljung-Box Q statistic for the hypothesis that there is no serial correlation up to order of 5 is 19.31 with a significant p-value of 0.00 which indicates that we have autocorrelation problem of higher order. However, unlike Nifty monthly Nifty Junior returns exhibits autoregressive conditional heteroskedasticity (ARCH) effects.

Table 11: Results of Equation (7) for Nifty Junior corrected for autocorrelation and ARCH Effect

Mean Equation			
Variables	Coefficients	t-statistic	P-Value
Intercept	1.9045	0.85	0.39
June	-4.67	-1.93	0.05
July	2.3638	0.48	0.62
August	0.6749	0.17	0.86
September	0.253	0.06	0.94
October	-2.9230	-0.80	0.42
November	0.038	0.01	0.99
December	5.86	1.69	0.08
January	2.7228	0.70	0.47
February	-1.2328	-0.33	0.74
March	-2.7668	-1.01	0.31
April	-0.7839	-0.29	0.76
AR(1)	0.364	4.08	0.00
Variance Equation			
C	8.13		0.11
ARCH(1)	0.1648		0.10
GARCH(1)	0.7393		0.00
F-stat = 1.73(0.04) Ljung –Box Q (5) = 2.07 (0.72)			
ARCH LM Test(1): F- stat = 0.0142 (0.9051)			
Note: Figures in () are p-values			

Table 11 shows that after correcting for serial autocorrelation and ARCH effect, we found *June and December effect* in monthly Nifty Junior returns because the coefficient of these dummy variables are found statistically significant at 5 and 10 percent respectively. The F-statistic shows that at least one beta coefficient is different from zero. The Ljung-Box Q statistic shows that there is no pattern in residual. ARCH LM test also indicate that there is no ARCH effect in residual now.

9.0 Conclusion

In this study, we tried to examine the seasonality of stock market in India. We considered the S&P CNX Nifty as the representative of stock market in India and tested whether seasonality are present in Nifty and Nifty Junior returns using daily and monthly data sets. The study found that daily and monthly seasonality are present in Nifty and Nifty Junior returns. The analysis of stock market seasonality using daily data, we found Friday Effect in Nifty returns while Nifty Junior returns were statistically significant on Friday, Monday and Wednesday. In case of monthly analysis of returns, the study found that Nifty returns were statistically significant in July, September, December and January. In case of Nifty Junior, June and December months were statistically significant. The results established that the Indian stock market is not efficient and investors can improve their returns by timing their investment.

References

1. Agrawal, Anup, and Kishore Tandon (1994), “Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries,” *Journal of International Money and Finance*, Vol. 13, pp. 83–106.

2. Ariel, Robert A.(1987), “A Monthly Effect in Stock Returns,” *Journal of Financial Economics*, Vol. 18, pp. 161–74.

3. Ariel, Robert. A.(1990), “High Stock Returns before Holidays: Existence and Evidence on Possible Causes,” *Journal of Finance*, Vol. 45, pp. 1611–25.

4. Bodla, B.S.and Kiran Jindal (2006), “Seasonal Anomalies in Stock Returns: Evidence from India and the US, Decision, Vol. 33. No.1 pp. 46-55.

5. Brooks, Chris, and Gita Persand (2001), “Seasonality in Southeast Asian Stock Markets: Some New Evidence on Day-of-the-Week Effects,” *Applied Economic Letters*, Vol. 8, pp. 155–58.

6. Brown, P., D.B. Keim, A.W. Keleidon, and T.A. Marsh (1983), “Stock Return Seasonalities and the Tax-Loss-Selling-Hypothesis: Analysis of the Arguments and Australian Evidence,” *Journal of Financial Economics*, Vol. 12, pp.105-127.

7. Cadsby, Charles Bram, and Mitchell Ratner (1992), “Turn-of-the-Month and Pre-Holiday Effects in Stock Returns,” *Journal of Banking and Finance*, Vol. 16, pp. 497–509.

8. Choudhary, K and Sakshi Choudhary (2008), “Day-of-the-Week Effect: Further Empirical Evidence”, Asia-Pacific Business Review, Vol. 4, no.3, pp.67-74.

9. Choudhary, T. (2001), “ Month of the Year Effect and Januray Effect in pre-WWI stock returns: Evidence from a non-linear GARCH”, *International Journal of Finance & Economics,* 6, pp.1-11.

10. Cross, Frank (1973), “The Behavior of Stock Prices on Fridays and Mondays,” *Financial Analysts Journal*, November–December, pp. 67–69.

11. Fama, Eugene F.(1970) “Efficient Capital Markets: A Review of Theory & Empirical Work,” *Journal of Finance*, pp. 383-417.

12. Husain, Fazal (1998), "A Seasonality in the Pakistani Equity Market: The Ramdhan Effect”, *The Pakistan Development Review,* Vol. 37 no.1, pp. 77-81.

13. Fountas, Stilianos and Konstantinos N. Segredakis(2002) "Emerging stock markets return seasonalities: the January effect and the tax-loss selling hypothesis", *Applied Financial Economics*, Vol. 12, pp. 291-299.

14. Gibbons, Michael R., and Patrick Hess (1981), "Day-of-the-Week Effects and Asset Returns," *Journal of Business*, Vol. 54, pp. 579–96.

15. Gultekin, M.N., and N.B. Gultekin (1983) "Stock Market Seasonality: International Evidence," *Journal of Financial Economics*, Vol.12, pp. 469-481.

16. Hirsch,Y. (1968), "The Stockholder's Almanac", *The Hirsch Organization, Old Tappan N. J.*

17. Jaffe, Jeffrey F., and Randolph Westerfield and M. Christopher (1989), "A Twist on The Monday Effect in Stock Prices: Evidence from the U.S. and Foreign Stock Markets," *Journal of Banking and Finance*, Vol. 13, pp. 641-650.

18. Keim, D.B.(1983),"Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence," *Journal of Financial Economics*, Vol.12, pp.13-32.

19. Keim, D.B.(1989), "Trading patterns, bid-ask spreads, and estimated security returns : The case of common stocks at calendar turning points", *Journal of Financial Economics*, Vol 25, no. 1, pp. 75-97.

20. Kelly, F., (1930), "Why You Win or Lose: The Psychology of Speculation", *Boston: Houghton Mifflin.*

21. Kumari, D. and Mahendra, R.(2006) "Day-of-the-week and other market anomalies in the Indian stock market". *International Journal of Emerging Markets*, Vol.1, no.3, pp.235-246.

22. Lakonishok Josef and Seymour Smidt (1988), " Are seasonal Anomalies real? A ninety years perspective, *The Review of Financial Studies*, Vol. 1, No. 4. pp. 403-425.

23. Li L. Ong & Jason D. Mitchell, (2006), "Seasonalities in China's Stock Markets: Cultural or Structural?", IMF Working Paper, IMF.

24. Mills, T.C., Coutts, J.A. (1995), "Calendar Effects in the London Stock Exchange FTSE Indices", European Journal of Finance, no.1, pp.79-93.

25. Pandey I M (2002). "Is There Seasonality in the Sensex Monthly Returns," IIMA Working Paper, IIM Ahmedabad.

26. Poterba, James M. and Scott J. Weisbenner (2001), “Capital Gains Tax Rules, Tax-Loss Trading, and Turn of the Year Returns, *The Journal of Finance*, Vol. 56, no. 1, pp. 353-368.

27. Raj, M., Thurston, D. (1994), "January or April? Tests of the turn-of-the-year effect in the New Zealand stock market", *Applied Economic Letters*, Vol. 1, pp.81-93.

28. Reinganum, M.R.(1983) “The Anomalous Stock Market Behavior of Small Firms in January Empirical Test for Year-End Tax Effect,” *Journal of Financial Economics*, Vol. 12, pp.89-104.

29. Rozeff, Michael S., and William R. Kinney (1976), “Capital Market Seasonality: The Case of Stock Market Returns, “ *Journal of Financial Economics*, Vol. 3, pp. 376-402.

30. Samuelson, Paul. A (1965), “Proof That Properly Anticipated Prices Fluctuate Randomly” Industrial Management Review, Vol.6, no. 2, pp. 41.

31. Schwert, G. William (2002), “Anomalies and Market Efficiency”, *Handbook of the Economics of Finance*, pp. 937-972.

32. Smirlock, Michael, and Laura Starks (1986) “Day of the Week and Intraday Effects in Stock Returns,” *Journal of Financial Economics*, Vol. 17, pp. 197-210.

33. Wachtel, S.B. (1942),“Certain Observation on Seasonal Movement in Stock Prices,” *Journal of Business*, Vol. 15, pp.184-193.

34. Zeimba, W.T. (1991), “Japanese Security Market Regularitie: Monthly, Turn of the Month and Year, Holiday and Golden Week Effects” Japan and World Economy , no.3, pp. 119-146