Seasonality in Emerging Economies: Evidences from Indian Stock Market

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Abstract

A great deal of research was devoted to investigating the randomness of stock price movements for the purpose of demonstrating the efficiency of capital markets. More recently, however researchers have demonstrated market inefficiency by identifying systematic variations in stock returns. These are called as calendar anomalies or stock market anomalies. The existence of seasonality or monthly effects in domestic and international markets suggests a market inefficiency, in that investors should be able to earn abnormal rates of return incommensurate with the degree of risk. Thus, this study focuses on stock market anomalies or calendar anomalies in Indian stock market. The results established are that the Indian stock market is not efficient and investors can improve their returns by timing their investment.

Keywords: Market Efficiency, Stock Market Anomalies, Seasonality, Efficient Market Hypothesis

1. Introduction

Even in efficient markets, where security prices accurately reflect all relevant and recent information, many well-documented seasonal effects continue to exist in many markets. Conventional wisdom states that the stock market is random, that is, there are no patterns or mechanisms which can be understood and used to consistently predict market movements up or down. The theory of market seasonality states just the opposite. This theory holds that there are real factors operating on the stock market which cause consistently recurring patterns over decades of market history. These factors can be used as the basis for an improved, less risky, investment method. "Seasonality" is used to define a number of seasonal trends that seem to exist in the stock market. A "seasonal trend" is a recurrent time period when the stock market has a statistically high tendency to either rise or fall. Timing the market perfectly is nearly impossible and investors who trade frequently pay more commissions, but do not necessarily make more money. Furthermore, there is a difference between market timing and factoring in seasonality in investment decisions. Market timing is based on short-term price patterns and trying to pick market tops and bottoms.

Seasonality is about anticipating how the market will behave in a given time of year and taking a position before the change occurs (e.g., if I know that December and January are usually strong then I may invest in November to make sure that I hold my investments in the following months). Actually, a (consistent) seasonal pattern represents evidence against the weak-form market efficiency since it would imply return predictability. At a practical level, investors can build trading strategies based on consistent seasonality or, at least, they can determine favourable market entry and exit moments.

Many kinds of calendar "anomalies" have been found but the most popular (or recurrent) are the Day-of-the week effect (or Weekday effect, Weekend effect, or most of the times, the Monday effect), the January effect (or Turn-of-the-year effect, the Turn-of-the month effect) and the Holiday effect.

When evaluating valuation levels and the technical outlook of stock markets, one should also take cognizance

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of seasonality but understand that it is not a stand-alone indicator and it is anybody's guess whether a specific year will conform to the historical pattern.

2. Review of Literature

The dictionary defines anomaly as something inconsistent with what is naturally expected. Seasonality in stock market or calendar anomalies in stock markets have been extensively researched in the finance literature. Researches has revealed that there are predictable times during which stocks as whole and certain other stock in particular outperform the market. The most common anomalies are the day-of-the-week effect, the weekend effect and the January effect. The theory of efficient market hypothesis states that the prices of the financial assets reflect all relevant information. A direct consequence is that an active investor cannot continuously beat the market and a passive investor can achieve the same profit in average as the active does. But the theory has begun to show a few cracks, referred to as anomalies and empirical evidence indicates that the efficient market hypothesis may not always be generally applicable.

Stock Market Seasonality: A study on Indian stock market is a research done by Ash Narayan Sah (2009) on stock market seasonality. It had the objective of finding day of the week, weekend effect, monthly effect on the returns of S&P CNX Nifty and CNX Nifty Junior during the period April 1947 to March 2009. The study revealed 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.

The month of the year effect postulates that stock returns on a particular month are higher than the other months. In developed markets, many empirical studies have confirmed January Effect, where mean stock returns are significantly higher in January than the rest of the year (Ben et.al.(2011)). Over long periods of time, stock prices have tended to experience an abnormal rise from December to January that is predictable and some say it is due to tax issues.

The study conducted by Denis (1995) on seven countries shows that three of these had a monthly effect. It was also determined that the January Effect, although significant, was not capable of explaining the presence of the monthly effect where they exist.

Study by Ushad Subadar (2008) on Stock Exchanges of Mauritius, reveals that returns on an average are lowest in the month of March and highest in the month of June.

Nousheen et.al. (2010) studied the Karachi Stock Exchange and found that there were significant returns in the month of May however these were negatively significant returns which showed that in month of May trading volumes remain low and thus negative returns occur to investors as compared to January.

It has been well documented that the returns on many securities vary by the day of the week. There is nothing in financial theory to explain why returns on Thursday should be different from returns on Tuesday or Wednesday. Nonetheless, a great deal of evidence shows that returns differ depending on the day of the week.

Ercan Balaban (1994) revealed that daily anomalies in stock market are international phenomenon and that the daily seasonal are not constant in the direction and magnitude through different time periods. Studies conducted by Talat et.al (2011) on emerging equity market of Saudi Arabia confirms that mean daily returns are significantly different from each other and validate the day of the week effect in Tadawul. Nik et.al.(2010) studied Malaysian stock market which revealed that day of the week effect was present in the Malaysian Market. It also indicated that Monday had a lower average return than Friday.

According to the weekend effect, the average daily returns of the market are not the same for all days of the weeks, something we would expect in an efficient market. It is used to describe a phenomenon in financial markets in which stock returns on Monday are often lower than those of immediately preceding Friday of many seasonal anomalies, very few are quite as perplexing and as well researched as the anomaly of positive Friday negative Monday returns called as weekend effect. It has been found in markets worldwide and has been extensively documented by Fama (1965), Cross (1973), French (1980), Lakonishok and Smidt (1989), and Abhraham and Ikenberry (1994). A study conducted by Boudreaux (2008) supports a weekend effect but only during nonbear market orientations. Jeffrey and Randolph (1984) examined daily stock market returns for the USA, UK, Japan, Canada and Australia and found weekend effect in each country . The study conducted by Jorge et.al (2005) documents evidence that traditional weekend effect tends to be associated with small firms while the 'reverse weekend effect' tends to be associated with large firms. The scope of this study will include day of the week effect, weekend effect and monthly effect in stock returns of S&P CNX Nifty.

3. Statement of the Problem

A great deal of research was devoted to investigating the randomness of stock price movements for the purpose of demonstrating the efficiency of capital markets. More recently, however researchers have demonstrated market inefficiency by identifying systematic variations in stock returns. These are called as calendar anomalies or stock market anomalies. The existence of calendar or time anomalies is a contradiction to the weak form of the Efficient Market Hypothesis (EMH). The weak form of the EMH states that the market is efficient in past price and volume information, and stock movements cannot be predicted using this historic information. This form infers that stock returns are time invariant, that is, there is no identifiable short-term time based pattern. The existence of seasonality or monthly effects in domestic and international markets suggests a market's inefficiency, in that investors should be able to earn abnormal rates of return incommensurate with the degree of risk. Thus it is necessary that stock market anomalies or calendar anomalies to be studied.

4. Objectives of the Study

- To study day of the week effect in returns of S&P CNX Nifty.
- To study weekend effect in returns of S&P CNX Nifty.
- To study monthly effect in returns of S&P CNX Nifty.

4.1 Hypotheses

- H1: The returns on all the days of weeks are equal.
- H2: Returns on Friday is lower than returns on Monday.
- H3: Returns of all the months in a year are equal.

4.2 Methodology

Descriptive research design was used for this study. Return on S&P CNX Nifty constitutes the population for this study. Return on S&P CNX Nifty is calculated for a period of 10 years, from 03 January 2002 to 31 December 2012. The daily prices of S&P CNX Nifty are collected from website of NSE. The monthly average price of S&P CNX Nifty is collected from Handbook of Statistics on Indian Economy for various years including 2010-2011 and 2011-12 published by RBI

To find out the existence of stock market seasonality in India, first find the stock market return of S&P CNX Nifty using the formula

$$R_t = (\text{In } P_t - \text{In } P_{t-1}) * 100$$

where, R_t is the return in period t, P_t and P_{t-1} are the monthly (daily) closing prices of the S&P CNX Nifty at time t and t-1 respectively. It is also important to test stationarity of a series otherwise the regression results will be spurious. Therefore, it is necessary to test whether Nifty return is stationary by using AR(1) model. The main statistical tool that is used in this study is ANOVA.

5. Data Analysis

Stationarity of the series is tested to know whether Nifty return is stationary using AR(1) model. AR(1) is abbreviation for a first order auto regression. The correlation of series with its own lagged values is called autocorrelation or serial correlation. The first autocorrelation is the correlation between Y_t and Y_{t-1}, that is correlation between values of Y at 2 adjacent dates. An autoregression is regression of a series with its own lag. AR(1) model equation is equal to

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + u_t$$

where β_0 and β_1 are unknown and estimated using historical data, u_t is the error term.

For finding AR (1) model the study uses ARIMA model. ARIMA models are, in theory, the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging. In fact, the easiest way to think of ARIMA models is as fine-tuned versions of random-walk and random-trend models: the fine-tuning consists of adding lags of the differenced series and/or lags of the forecast errors to the prediction equation, as needed to remove any last traces of autocorrelation from the forecast errors.

The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. Random-walk and random-trend models, autoregressive models, and exponential smoothing models (i.e., exponential weighted moving averages) are all special cases of ARIMA models.

A non-seasonal ARIMA model is classified as an "ARIMA(p,d,q)" model, where:

p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors in the prediction equation.

Autocorrelation of series is calculated using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). To test the presence of seasonality in stock returns of Nifty, the study has used dummy variable regression model. This technique is used to quantify 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.

Donald B. Keim (1983) suggested a regression model with dummy variables as a method of testing the January effect.

$R_t = \alpha + \sum b_t D_t + e$

where: Dt represents monthly and daily returns

The intercept constant α represents benchmark day or month

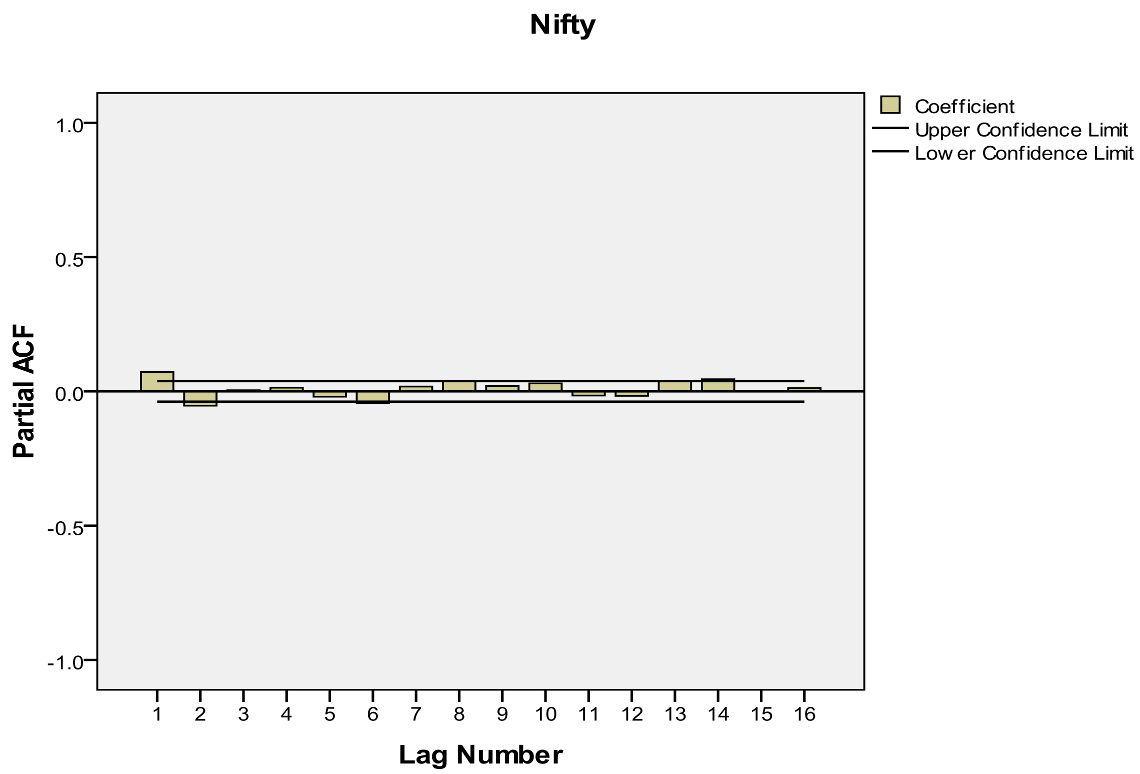
e is the error term or white noise.

Table 1: Autocorrelations

Series:Nifty					
Lag	*Autocorrelation*	*Std. Error*[a]	*Box-Ljung Statistic*		
			Value	*df*	*Sig.*[b]
1	.072	.019	14.193	1	.000
2	-.048	.019	20.436	2	.000
3	-.003	.019	20.465	3	.000
4	.016	.019	21.201	4	.000
5	-.017	.019	22.015	5	.001
6	-.048	.019	28.288	6	.000
7	.013	.019	28.738	7	.000
8	.045	.019	34.283	8	.000
9	.024	.019	35.878	9	.000
10	.028	.019	37.968	10	.000
11	-.011	.019	38.316	11	.000
12	-.018	.019	39.231	12	.000
13	.034	.019	42.374	13	.000
14	.048	.019	48.765	14	.000
15	.002	.019	48.772	15	.000
16	.007	.019	48.912	16	.000

a. The underlying process assumed is independence (white noise).
b. Based on the asymptotic chi-square approximation.
Source: SPSS Results

Figure 1: Partial Autocorrelation Function



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 used in the study:

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

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 the study, μ is the error or white noise.

Similarly, to find whether there are monthly effects in Nifty returns, ANOVA model is used and is specified as below:

Nifty Returns= $\alpha + \beta_1 D_{Jan} + \beta_2 D_{Feb} + \beta_3 D_{Mar} + \beta_4 D_{May} + \beta_5 D_{June} + \beta_6 D_{July} + \beta_7 D_{Aug} + \beta_8 D_{Sep} + \beta_9 D_{Oct} + \beta_{10} D_{Nov} + \beta_{11} D_{Dec} + \mu$

Where α is benchmark month of April and μ represents the error or white noise.

Y = Monthly returns of Nifty, D1= 1 if the month is January; 0 otherwise, D2 = 1 if the month is February; 0 otherwise, D3 = 1 if the month is March; 0 otherwise, D4 = 1 if the month is May; 0 otherwise, D5 = 1 if the month is June; 0 otherwise, D6 = 1 if the month is July; 0 otherwise, D7 = 1 if the month is August; 0 otherwise, D8 = 1if the month is September; 0 otherwise, D9 = 1 if the month is October; 0 otherwise, D10 = 1 if the month is November; 0 otherwise, D11 = 1 if the month is December; 0 otherwise.

6. Days of the Week Effect and Weekend Effect

Box- L jung tests randomness of a series. Table 1 indicates that the series is free from randomness till the lag of 16. Box – Ljung statistics should have significance value of less than 0.05 for all or almost all lags. This criterion is met in this series.

The graph given in Figure 1 analyses the Partial Autocorrelation Function. It another useful method to examine serial dependencies is to examine the partial autocorrelation function (PACF) - an extension of autocorrelation, where the dependence on the intermediate elements (those within the lag) is removed. From the given graph it is found that the series are within the critical value of acceptance that is within 0.05 and -0.05. But in the data it is seen that the lag 1 value is slightly higher than other values in series, which is the reason why AR (1) model is chosen to analyze autoregression in the series. The PACF plot has a significant spike only at lag 1, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation. The PACF of the UNITS series provides an extreme example of the cut-off phenomenon: it has a very large spike at lag 1 and no other significant spikes, indicating that *in the absence of differencing* an AR(1) model should be used.

From the data in Table 2 and 3, it is found that the R^2 is 0.001 which is very low. P value for the model is 0.603 which means that the model is not significant.

From Table 4 it is seen that none of the variables are significant. It is found that there exists autocorrelation in this, therefore ARIMA model fits to this series. After this, a new variable called Noise residual is created. Then regression is again performed on this series but this time variable noise residual is added to independent variables. After this is done the regression is found.

R^2 has improved a lot, that is about 0.995 indicating that 99.5 percent of variation in dependent variable is explained by independent variable. ANOVA significance for the model is below 0.05 indicating the model is significant.

In coefficients table (Table 7) it is found that Thursday is not significant. Since all other variables have significance value less than 0.05, take their B values into consideration. From this it is found that returns on Monday is more significant than returns on Friday (constant) value as Monday's B value is less than Friday. So the returns on Monday are significant. Next it is found that value of returns of Tuesday, wherein B is more than of returns of Monday indicating that returns of Tuesday is not significant. The B value of Wednesday should be more than Tuesday and since it is true returns of Wednesday is also significant. We also find that there exist Monday effect and Wednesday effect indicating that there is day of the week effect in S&P CNX Nifty. Thus the study indicates that returns on all the days of the week are not equal and there exists day of the week anomaly.

From the study it is found that returns of Monday is more significant than Friday (constant value) as Monday's

Table 2: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.032[a]	.001	.000	1.71249

Predictors: (Constant), Thursday, Monday, Tuesday, Wednesday

Source: SPSS Results

Table 3: ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.021	4	2.005	.684	.603[a]
	Residual	8044.207	2743	2.933		
	Total	8052.228	2747			

a. Predictors: (Constant), Thursday, Monday, Tuesday, Wednesday
b. Dependent Variable: Nifty
Source: SPSS Results

Table 4: Coefficients[a]

Model						
B		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		Std. Error	Beta			
1	(Constant)	.059	.073		.805	.421
	Monday	-.064	.103	-.015	-.616	.538
	Tuesday	-.058	.103	-.014	-.564	.573
	Wednesday	.086	.103	.020	.832	.406
	Thursday	-.019	.103	-.004	-.180	.857

a. Dependent Variable: Nifty

Source: SPSS Results

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.997a	.995	.995	.12482

a. Predictors: (Constant), Noise residual from Nifty-Model_1, Thursday, Monday, Tuesday, Wednesday
Source: SPSS Results

Table 6: ANOVA[b]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	8000.268	5	1600.054	102701.606	.000[a]
	Residual	42.704	2741	.016		
	Total	8042.972	2746			

a. Predictors: (Constant), Noise residual from Nifty-Model_1, Thursday, Monday, Tuesday, Wednesday
b. Dependent Variable: Nifty
Source: SPSS Results

Table 7: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error		Beta	t	Sig.
1	(Constant)	.056	.005		10.536	.000
	Monday	-.059	.008	-.014	-7.833	.000
	Tuesday	-.045	.008	-.010	-5.923	.000
	Wednesday	.081	.008	.019	10.754	.000
	Thursday	-.014	.008	-.003	-1.849	.065
	Noise residual from Nifty-Model_1	1.000	.001	.997	716.249	.000

aDependent Variable: Nifty
Source: SPSS Results

B value is less than Friday. Since the returns of Friday should be more significant than returns on Monday so as to show week end effect. The study indicates that there is no weekend effect in this study.

Table 7 indicates that the series is free from randomness till the lag of 11. Box – Ljung statistics should have significance value of less than 0.05 for all or almost all lags. This criterion is met in this series as majority of lag is free from randomness.

Table 8: Model Summary

Model	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
1	.254[a]	.064	-.021	6.90056

a. Predictors: (Constant), December, November, October, September, August, July, June, May, January, March, Feb
Source: SPSS Results

Table 9: ANOVA[b]

Model		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
1	Regression	392.753	11	35.705	.750	.689[a]
	Residual	5714.128	120	47.618		
	Total	6106.881	131			

a. Predictors: (Constant), December, November, October, September, August, July, June, May, January, March, Feb
b. Dependent Variable: Monthly_Nifty
Source: SPSS Results

Table 10: Autocorrelations

Series: Monthly_Nifty					
Lag	*Autocorrelation*	*Std. Error*[a]	*Box-Ljung Statistic*		
			Value	*df*	*Sig.*[b]
1	.329	.086	14.596	1	.000
2	-.030	.086	14.715	2	.001
3	.112	.085	16.441	3	.001
4	.032	.085	16.586	4	.002
5	.014	.085	16.614	5	.005
6	-.080	.084	17.506	6	.008
7	-.107	.084	19.132	7	.008
8	-.038	.084	19.334	8	.013
9	-.058	.083	19.824	9	.019
10	-.016	.083	19.859	10	.031
11	.019	.083	19.911	11	.047
12	-.037	.082	20.109	12	.065
13	.024	.082	20.191	13	.091
14	-.015	.082	20.223	14	.123
15	-.114	.081	22.205	15	.103
16	-.008	.081	22.214	16	.136

a. The underlying process assumed is independence (white noise).
b. Based on the asymptotic chi-square approximation.
Source: SPSS Results

7. Monthly Effect

It is seen that the series are within the critical value of acceptance that is within 0.05 and -0.05. But the lag 1 value is slightly higher than other values in series, which is the reason why AR(1) model is chosen to analyze autoregression in the series. The PACF plot has a significant spike only at lag 1, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation. The PACF of the UNITS series provides an extreme example of the cut-off phenomenon: it has a very large spike at lag 1 and no other significant spikes, indicating that *in the absence of differencing* an

AR(1) model should be

From the data given in Tables 8, 9 and 10, it is found that the R^2 is 0.064 which is very low. ANOVA significance for the model is 0.689 which means the model is not significant.

From Table 11, it is seen that none of the variables are significant. There exist autocorrelation in this, therefore ARIMA model fits to this series. After this,a new variable called Noise residual is created. Then regression on this series is performed and noise residual is added to independent variables. After this, the regression is found.

It is seen that R^2 has improved a lot that is about 0.896 indicating that 89.6 of variation in dependent variable is explained by independent variable. ANOVA significance for the study is below 0.05 indicating the model is significant.

From Table 11, it is found that March, September and December are significant as their significance value is less than 0.05. This indicates that anomalies exist in these months. Thus the study indicates that the returns on all months are not equal, thus indicating there exist month anomalies.

8. Discussions And Results

The following are the findings from this study

- The study indicates that there exist day of the week anomaly in S&P CNX Nifty as Monday and Wednesday are significant. It shows that there exist a Monday Effect and Wednesday Effect in S&P CNX Nifty.
- The study was unable to find a Weekend Effect in S&P CNX Nifty.

Table 11: Coefficients[a]

Model						
		Unstandardized Coefficients		*Standardized Coefficients*	*t*	*Sig.*
		B	*Std. Error*	*Beta*		
1	(Constant)	.818	2.081		.393	.695
	January	1.425	2.942	.058	.484	.629
	Feb	-.736	2.942	-.030	-.250	.803
	March	-3.192	2.942	-.130	-1.085	.280
	May	-1.192	2.942	-.048	-.405	.686
	June	-.914	2.942	-.037	-.311	.757
	July	.537	2.942	.022	.183	.855
	August	1.064	2.942	.043	.362	.718
	September	1.982	2.942	.081	.674	.502
	October	-.900	2.942	-.037	-.306	.760
	November	1.412	2.942	.057	.480	.632
	December	3.655	2.942	.149	1.242	.217

a Dependent Variable: Monthly_Nifty
Source: SPSS Results

Table 12: Model Summary

Model	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
1	.947[a]	.896	.886	2.29881

a. Predictors: (Constant), Noise residual from Monthly_Nifty-Model_1, November, January, June, July, May, August, September, October, March, December, Feb
Source: SPSS Results

Table 13: ANOVA[b]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	5378.570	12	448.214	84.817	.000[a]
	Residual	623.572	118	5.285		
	Total	6002.143	130			

a. Predictors: (Constant), Noise residual from Monthly_Nifty-Model_1, November, January, June, July, May, August, September, October, March, December, Feb
b. Dependent Variable: Monthly_Nifty
Source: SPSS Results

Table 14: Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.815	.693		1.175	.242
	January	.667	1.004	.026	.664	.508
	Feb	-.786	.980	-.032	-.802	.424
	March	-3.184	.980	-.130	-3.248	.002
	May	-1.189	.980	-.049	-1.213	.228
	June	-.911	.980	-.037	-.929	.355
	July	.540	.980	.022	.551	.582
	August	1.068	.980	.044	1.089	.278
	September	1.987	.980	.081	2.027	.045
	October	-.892	.980	-.037	-.910	.365
	November	1.430	.980	.059	1.459	.147
	December	3.701	.980	.152	3.775	.000
	Noise residual from Monthly_Nifty-Model_1	1.000	.033	.913	30.762	.000

a. Dependent Variable: Monthly_Nifty
Source: SPSS Results

- The study on monthly series of S&P CNX Nifty indicates that there exists Monthly Effect in the index. There exist March Effect, September Effect and December Effect as anomalies in the S&P CNX Nifty.

The results established are that the Indian stock market is not efficient and investors can improve their returns by timing their investment. The results are important for both traders and investors who base their investment strategies and decisions on the general index of S&P CNX Nifty. In addition, these findings may have a favourable impact on attracting foreign investment to S&P CNX Nifty market given the weak-form efficient market hypothesis for the market is not rejected. Finally, as the knowledge of monthly anomaly, day of the week anomalies and other market anomalies is useful for the investors in the S&P CNX Nifty; future research might find it interesting to investigate further this anomaly as well as other time anomalies and find out what are the reasons for such anomalies.

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