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Security Returns Spectrum- An Analysis of Seasonality and Sensitivity of Indian Stock Markets

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Abstract

Calendar anomalies have been found to be prevalent in major markets throughout the world. The thesis extends the existing literature on calendar anomalies by considering indices (broad and sectoral) over a longer time frame. The specific comparisons between multiple indices helped retest the conclusions on several calendar anomalies examined previously in other countries but not analyzed in Indian Stock markets to reach conclusion with few confounding factors. The results were modelled using econometric models to handle the issues of normality in the univariate time series analysis. The results obtained show 360 degree causal relationship, interlinking one calendar anomaly results with other anomalies more so in the recent times. The results obtained also show calendar anomalies converging with patterns observed across major global economies.

Keywords & Phrases: Seasonality, Anomalies, Econometric models and Indices.

1.0 Introduction

A phenomenon can be global in nature, only if, it has the capability to cut across borders, by truly adapting itself to the regional diverse factors and most importantly, capable of giving identical results. The markets become truly integrated, when the advancements in satellite technology made it possible for everyone, anywhere, in the world to receive uninterrupted information consistently and competitively. Information Technology and Institutional advancements facilitated dissemination of information quickly across economies and thus helped to understand and recognize the true intrinsic values of asset prices and to find various opportunities which were truly global in nature. Inspite of these advancements a phenomenon which has consistently baffled researchers across various disciplines, by being mysterical in nature, irrespective of abundant literature available has been the “patterns in stock returns”.

The current stock market prices are often considered to be the indicators of investors’ current and future expectations. The patterns in stock returns reflect these expectations of the investors which might be based on rational and seemingly irrational behavior.

Considering this, the stock markets would then be considered as the indicators of future economic trends.

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The presence of patterns in stock returns through empirical analysis is found to be complex to explain, and do not agree with the current asset pricing theories. These price change predictions or patterns, known as anomalies, can be an indication for investors to adopt unique trading strategies to make abnormal profits, or an indication of errors in current asset-pricing theories. The study tries to examine the former possibility, which violates the idea of market efficiency. The EMH is considered to be the central paradigm in finance. According to EMH, past prices of shares should have no predictive power in judging the future prices. The EMH relates to how quickly and accurately the market reacts to new information. New information refers to new data which constantly enters the market such as government's reforms, economic reports, company announcements, political statements, or public surveys. If markets are informationally efficient, then security prices would incorporate the new information rapidly and accurately. In particular, stock returns would follow a random walk, which is unpredictable and without pattern. The market inefficiencies have been generally, documented in three categories. The first category is based on the belief that employing specific trading strategies based on past information which are freely available to all investors can be utilized in making extraordinary profits. But, excess returns should vanish when investors as a whole massively make decisions on such information. The second category believes in earning abnormal returns by selecting stocks based on firm based information which is also freely available to all investors. The third category of market inefficiency has been documented to make extraordinary profits by analyzing the unexpected return patterns due to news announcements such as calendar based news, which is the research theme of the study. Studies on empirical regularities in security returns have rejected the hypothesis of markets being efficient and models especially, the asset pricing models to be not adequate. These results have paved way for research on explaining the market anomalies. The studies spanning nearly a century provided very interesting but, versatile explanation to the occurrence of seasonal anomalies which were unique to respective markets across the globe. The initial investigations however, provided evidence of seasonal anomalies in the U.S. capital markets and other developed markets but the pattern and types of anomalies varied from one study to another. With further investigations, the presence of calendar anomalies was understood to be omnipresent occurring in stock markets throughout the world. Thus the empirical investigations on the behavior of the stock market patterns across the world have raised several interesting questions about market efficiency of several developed and developing economies. The search for an explanation of stock market anomalies, however, has largely been unsuccessful. None of the attempts to modify the Capital Asset Pricing Model (CAPM) to account for taxation, transaction costs, skewness of preference and asymmetric information adequately explain the anomalies. Thus, our understanding of the economic or statistical causes of the apparent excess returns generated by anomalies is incomplete.

2.0 Review of Literature

The following calendar effects are taken into account for the study namely: The month-of-the-year effect, the day-of-the-week effect, the turn-of-the-month effect, the half-month effect, half-year effect and the Holiday effect were considered for study. The most important literature and possible explanations for the above mentioned calendar effects are summarized below;

2.1 Month-of-the-Year Effect

According to EMH, the mean stock returns spread over the different months of the year should be equal. The presence of seasonal patterns in the monthly returns is called the month-of-the-year effect. It is observed from the literature that numerous studies have been done on month-of-the-year effect. Wachtel (1942), Rozeff and Kinney (1976), Lakonishok and Smidt (1988), Rozeff and Kinney, Roll (1983), Keim (1983) and Reinganum (1983), Schwert (2003), Gultekin and Gultekin (1983), Agarwal and Tandon (1994) found the presence of January effect in U.S. and other developed economies. Though there exists abundant literature examining the presence of January effect, the explanation provided in the literature to the cause of January effect are not yet proven satisfactory across different countries. Some of the possible explanations to the presence of January effect are mainly the sample selection bias, tax-loss selling hypothesis, tax-loss selling hypothesis from the point of view of retail and institutional investors and portfolio revaluation by managers.

2.2 Day-of-the-week Effect

Day-of-the-week effect is the most discussed calendar anomaly in literature on calendar anomalies. Day-of-the-week effect states that the daily mean stock returns in context of an efficient market should be equally distributed over different days of the week. Any violation reflects irregularity and gives chances for investors to make profits by exploiting this difference. The well known anomaly is the weekend effect, which states that mean Monday returns are consistently negative while mean Friday returns are positive in nature. The Day-of-the-week effect was documented first by Fields (1930) in stock return pattern of Dow Jones Industrial Average (DJIA). It was observed that the stock returns were continuously positive from Friday to Saturday except for Monday returns. The patterns lead to higher closing prices on Fridays (Saturday, if trading day). Later various studies by researchers mainly French (1980), Fama (1965) Clark's (1973), Jaffe and Westerfield (1985), Agarwal and Tandon (1994), Lakonishok and Smidt (1988), Schwert (2003), Gu (2004), Gibbons and Hess (1981) added further evidence to the presence of the anomaly. Closed market effect, Settlement effect, market capitalization, announcements effect were some reasons considered for explanation of Monday effect.

2.3 Half-Month Effect

Half-month effect states that high returns primarily occur during the first half of the month, while the second half of the month mean returns are almost zero or negative. One of the earliest papers to document half-month effect was by Ariel (1987). He found that the last trading day of the past month and first nine days of the new month were having higher returns than the average returns of the month. Similarly later, Lakonishok and Smidt (1988), Jaffe and Westerfield (1989), Penman (1987) and Peterson (1990) Mills and Coutts (1995) examined the indices in major countries and found conclusive evidence of half-month effect. Though studies have been done in other countries, no conclusive evidence has been found. Very few explanations were noted to be the reasons for this anomaly such as dividend payments and contamination of the data considered, announcements on first half of the month. Buying decisions of investors around the end of the month. Throughout the literature, it has been found that inclusion of the last trading day of the month, which yields significantly higher returns than the average daily returns might by due to methodology used by Ariel in his study and there is little evidence in favor of this anomaly and little evidence to support it.

2.4 Turn-of-the-month Effect

Turn-of-the-month effect states that high positive returns are concentrated during the last and first trading days of each month. In evidence of the half-month effect, it was found that high positive returns seem to occur around the turn of the month especially significant high returns seem to occur on the last trading day of the month and first three trading days of the new month. Lakonishok and Smidt (1988) examined the anomaly and found turn-of-the-month to be independent of other anomalies and to persist in several sub-periods over the examined data frame. They observed that excluding January effect or turn of the year effect still resulted in significant turn-of-the-month anomaly. After the results obtained by Lakonishok and Smidt (1988), similar studies were conducted in other countries to the presence of the turn-of-the-month anomaly by Agarwal and Tandon (1994), Kunkel, Compton and Beyer (2003), Kallunki and Martikanen (2001), Jakobs and Levy (1988), Odgen (1987) etc. None of the explanation given are considered satisfactory for explaining the anomaly across developed and developing economies.

2.5 Holiday Effect

Holiday effect states that day preceding a holiday yields much higher stock returns compared to the average daily returns. The initial documentation of the holiday effect was done by Fields (1934). He argued that since depressed Monday returns is caused by market closing, the day after a holiday where markets are closed should also yield negative returns. But the results showed not seasonal patterns after the holidays. Similar studies by Lakonishok and Smidt (1988), Ariel (1990), Kim and Park (1994), Agarwal and Tandon (1994), Brockman and Michayluk (1998), Vergin and McGinnis (1999), Chong, Hudson, Keasey and Littler (2005), Pettengill (1989) found returns around holidays to be not a random occurrence but for which there is no conclusive or satisfactory explanation.

3.0 Problem Statement, Objectives and Hypotheses

3.1 Problem Statement

The literature review provides evidence that the research on calendar anomalies has received less attention and thus this lack of research in India on calendar anomalies across broader and sectoral markets makes study of calendar anomalies important and imminent. The literature has further revealed that there are a lot of calendar anomalies which have not been examined for their presence across broader and sectoral markets in the Indian Stock markets for a longer time frame. The Literature review clearly emphasizes that in examining the seasonality or calendar anomalies in emerging markets such as India, methodology should be more robust and should be able to capture the issues of normality, autocorrelation, heteroscedasticity etc. Since the seasonal effects are straightforwardly detectable in market indices or large portfolio of shares rather than in individual shares (Boudreaux, 1995) broader and sectoral indices should be considered for the study in investigating presence of seasonal anomalies which represent the broader and diverse sectors of Indian Economy. The specific comparisons between multiple indices would help study with fewer confounding factors and to reach a broader conclusion which is ignored in many earlier investigations. Further, it would be pertinent to retest the conclusions drawn by the earlier studies inview of the changes in the widereconomic scenario in India, widened choice of benchmark portfolios and methods of measurement and techniques. Thus considering the stock markets as the indicators of future economic trends, and price change predictions or patterns as indications for investors to adopt trading strategies to make abnormal profits, or indications of errors in asset pricing theories, the study tries to examine the former possibility of presence of calendar anomalies in the context of the Indian stock markets, which violates the idea of market efficiency. In case these anomalies exist and are apparent, differentiating from most other research, we would examine if investors would benefit from the results and use these results in investment decision-making.

In light of this backdrop, the following objectives and sub-objectives are arrived at for the current research investigation:

3.2 Objectives of the Study

3.2.1 To investigate the presence of calendar anomalies in Indian stock markets.

The sub-objectives are:

a. To investigate whether month-of-the-year effect is present in Indian stock markets.

b. To analyse the presence of turn-of-the-month effect in Indian stock markets.

c. To assess whether semi-month effect is present in Indian stock markets.

d. To look for whether half-year effect is present in Indian stock markets.

e. To identify whether holiday effect is present in Indian stock markets and

f. To search whether the weekend-effect is present in Indian stock markets.

3.2.2 To make appropriate suggestions to individual investors and institutional investors on various trading strategies in investment decision-making and to suggest possible policy changes required based on whether calendar anomalies exist in Indian stock markets.

3.3 Hypotheses of the Study

The study intends to test the following Null Hypotheses:

H_{01}: All months of the year have the same rate of return.

H_{02}: Mean returns during turn-of-the-month and rest of the month are same.

H_{03}: Mean returns between first half of the month and second half of the month are same.

H_{04}: Mean returns between first half of the year and second half of the year are same.

H_{05}: Mean returns during holidays and rest of the days are the same.

H_{06}: Mean returns on all the days of a week are equal.

4.0 Data Collection and Research Methodology

4.1 Sample Selection For The Study

In order to search for the presence of calendar anomalies, nineteen indices comprising of both broader and sectoral indices listed on the both BSE and NSE exchanges were considered for the study. Which are as follows:

S&P BSE SENSEX, S&P BSE CAPITAL GOODS (BSE-CG), S&P BSE CONSUMER DURABLES (BSE-CD), S&P BSE FMCG (BSE FMCG), S&P BSE HEALTHCARE (BSE HC), S&P BSE AUTO, S&P BSE METAL, S&P BSE Oil & Gas (BSE O&G), S&P BSE-PSU, BSE-TECH INDEX, BSE Mid-Cap, BSE Small-Cap INDEX, CNX NIFTY, CNX NIFTY JUNIOR, CNX MIDCAP, CNX IT, BANK NIFTY and CNX INFRA.

Literature review on seasonal anomalies conducted in India concentrate mainly on BSE Sensex and NSE CNX Nifty index respectively. Though these two indices are barometer of the performance of Indian economy, both the indices give more weightage to specific sectors as shown in Table 1 and Table 2. BSE Sensex gives more weightage to financial services sector, Fast Moving Consumer goods (FMCG) sector, Oil and Gas sector, Information technology and media & publishing sectors. Thus companies with large free float market capitalization can bias the movement of the BSE Sensex index prices. In order to concentrate on Mid-cap and Small-cap stocks which were given less importance in BSE Sensex, Mid-cap and Small-cap indices were formed. As observed from Table-2, financial services, Capital goods, Healthcare, Housing related companies are given more weightage based on free float in Mid-cap and Small-cap indices. If seasonal anomalies exist in Indian stock markets then the study has to be justified by generalizing the phenomenon across sectors first and then to the broader economy, which is the research gap. It was thus felt that the true presence of seasonal anomalies could be understood by considering sectoral indices study separately. To understand seasonal anomalies, it is necessary to understand if these sectors exhibited seasonal anomalies separately which inturn would have confounding effects on the broader indices.

Table 1: Sector-wise distribution of indices listed on BSE considered for the study

SECTORS/INDICES	BSE SENSEX	BSE MIDCAP	BSE SMALL CAP	BSE FMCG	BSE HC	BSE OIL AND GAS	BSE IT	BSE CD	BSE TECK	BSE PSU	BSE AUTO	BSE METAL	BSE CG
Finance	26.93	21.68	10.28	0	0	0	0	0	0	26.54	0	0	0
FMCG	14.61	7.79	5.05	100	0	0	0	0	0	0	0	0	0
Oil & Gas	13.72	2.38	1.67	0	0	100	0	0	0	31.04	0	0	0
Information Technology	13.11	5.7	4.97	0	0	0	100	0	74.07	0	0	0	0
Media & Publishing	13.11	2.55	2.9	0	0	0	0	0	7.56	0	0	0	0
Transport Equipments	9.95	7.67	4.28	0	0	0	0	0	0	0	100	0	0
Transport Services	9.95	2.39	0.9	0	0	0	0	0	0	1.09	0	0	0
Capital Goods	6.14	7.57	12.64	0	0	0	0	0	0	4.02	0	0	100
Chemical & Petrochemical	6.14	5.37	5.03	0	0	0	0	0	0	0	0	0	0
Consumer Durables	6.14	2.71	3.21	0	0	0	0	100	0	0	0	0	0
Diversified	6.14	1.74	1.92	0	0	0	0	0	0	0	0	0	0
Healthcare	5.17	10.18	5.73	0	100	0	0	0	0	0	0	0	0
Housing Related	5.17	7.81	10.61	0	0	0	0	0	0	0	0	0	0
Metal,Metal Products & Mining	4.96	2.01	6.39	0	0	0	0	0	0	19.83	0	100	0
Miscellaneous	4.96	2.49	8.5	0	0	0	0	0	0	2.04	0	0	0
Power	2.84	1.81	1.9	0	0	0	0	0	0	15.05	0	0	0
Telecom	2.58	0.68	1.68	0	0	0	0	0	18.37	0.1	0	0	0
Textile	2.58	1.47	4.54	0	0	0	0	0	0	0	0	0	0
Tourism	2.58	1.46	1.55	0	0	0	0	0	0	0	0	0	0
Agriculture	0	4.46	5	0	0	0	0	0	0	0.3	0	0	0
Other	13.72	0.06	1.25	0	0	0	0	0	0	0	0	0	0

Source: Author

Table 2: Sector-wise distribution of indices listed on NSE considered for the study

SECTORS/INDICES OF NSE	NSE NIFTY	NSE NIFTY JUNIOR	NSE MIDCAP	NSE IT	BANK NIFTY	NSE INFRASTRUCTURE
FINANCIAL SERVICES	28.53	30.12	17.28	0	100	0
ENERGY	15.71	4.83	9.78	0	0	32
IT	14.45	4.46	8.67	100	0	0
CONSUMER GOODS	13.14	19.51	7.24	0	0	0
AUTOMOBILE	7.84	5.31	5.39	0	0	0
PHARMA	5.16	7.5	6.09	0	0	0
CONSTRUCTION	4.95	0.75	6.38	0	0	36.23
METALS	3.92	3.3	9.29	0	0	0
CEMENT & CEMENT PRODUCTS	3.34	0	1.22	0	0	0
TELECOM	1.91	4.01	2.42	0	0	20.08
INDUSTRIAL MANUFACTURING	1.04	4.1	5.81	0	0	9.14
HEALTHCARE SERVICES	0	2.01	0	0	0	0
FERTILISERS & PESTICIDES	0	1.2	2.52	0	0	0
MEDIA & ENTERTAINMENT	0	3.57	4.05	0	0	0
SERVICES	0	7.56	8.51	0	0	2.55
CHEMICALS	0	1.77	5.35	0	0	0

Source: Author

4.2 Sources of Data and Period of Study

For the present study mainly secondary data was considered. The data used in the study are the daily closing values of the nineteen market indices listed on Bombay/Mumbai Stock Exchange (BSE) and National Stock Exchange (NSE). The data for nineteen indices were collected from PROWESS, a corporate database maintained by Center for Monitoring Indian Economy Private Limited (CMIE) and was checked for quality from respective stock exchanges website databases i.e., BSE India website (www.bseindia.com) and NSE India website (www.nseindia.com). Daily, weekly, monthly and yearly share price data of nineteen indices were considered for the study. The period of study for each of the indices has been shown in Table-3 below. The other information pertaining to the study was obtained from various websites, journals and books mentioned below in the references.

In order to study Holiday effect, Hindu Lunar Holidays during which the Indian stock markets especially BSE and NSE stock exchanges remain closed for trading were considered from the year 1990 to 2011 as shown in Table 4 below.

Sl.no	Index	Base Period	Base Index value	Date of Launch	Data for study
1	S&P BSE SENSEX	1978-79	100	Jan 1,1986	Feb1,1991 to july 31,2011
2	S&P BSE CAPITAL GOODS	Feb 1,1999	1000	August 9, 1999	Aug 9, 1999 to july 31,2011
3	S&P BSE CONSUMER DURABLES	Feb 1,1999	1000	August 9, 1999	Aug 9, 1999 to july 31,2011
4	S&P BSE FMCG	Feb 1,1999	1000	August 9, 1999	Aug 9, 1999 to july 31,2011
5	S&P BSE HEALTHCARE	Feb 1,1999	1000	August 9, 1999	Aug 9, 1999 to july 31,2011
6	S&P BSE IT	Feb 1,1999	1000	August 9, 1999	Aug 9, 1999 to july 31,2011
7	S&P BSE PSU	Feb 1,1999	1000	June 04,2001	June 04,2001 to july 31,2011
8	S&P BSE TECK	Apr 2,2001	1000	July 11,2001	July 11,2001 to july 31, 2011
9	S&P BSE AUTO	Feb 1,1999	1000	August 23, 2004	Aug 23, 2004 to july 31,2011
10	S&P BSE METAL	Feb 1,1999	1000	August 23, 2004	Aug 23, 2004 to july 31,2011
11	S&P BSE OIL AND GAS	Feb 1,1999	1000	August 23, 2004	Aug 23, 2004 to july 31,2011
12	S&P BSE MID CAP	2002-03	1000	Apr 11,2005	Apr 11,2005 to july 31,2011
13	S&P BSE SMALL CAP	2002-03	1000	Apr 11,2005	Apr 11,2005 to july 31,2011
14	CNX NIFTY	Nov 3, 1995	1000	Apr 3,1993	Nov 3,1995 to july 31, 2011
15	CNX NIFTY JUNIOR	Nov 3,1996	1000	Jan 1, 1997	Jan 1, 1997 to July 31, 2011
16	CNX MIDCAP	Jan 1, 2004	1000	Jan 1, 2005	Jan 1, 2005 to July 31, 2011
17	CNX IT	Jan 1,1996	1000	Jan 1, 1997	Jan 1, 1997 to July 31, 2011
18	BANK NIFTY	Jan 1, 2000	1000	Jan 1, 2000	Jan 1, 2000 to July 31, 2011
19	CNX INFRA	Jan 1, 2004	1000	August 23, 2004	August 23, 2004 to July 31, 2011

Table 3: Data on broader and sectoral indices considered for the study

Source: www.bseindia.com and www.nseindia.com

YEAR	MAHA SHIVARATRI	RAMA NAVAMI	RAMZAN ID	GANESH CHATURTHI	DUSSERA MAHANAVAMI	DIWALI-LAXMI PUJA	DIWALI- BALI PRATIPADA	BAKRID	GURU NANAK JAYANTHI	MOHURRAM
1990	23 March 1990	03 April 1990	27 April 1990	24 August 1990	28 September 1990	18 October 1990	19 October 1990	04 July 1990	07 November 1990	02 August 1990
1991	13 February 1991	24 March 1991	17 April 1991	11 September 1991	16 October 1991	05 November 1991	06 November 1991	23 June 1991	21 November 1991	23 July 1991
1992	02 March 1992	11 April 1992	04 April 1992	31 August 1992	06 October 1992	25 October 1992	26 October 1992	11 June 1992	14 November 1992	11 July 1992
1993	19 February 1993	01 April 1993	25 March 1993	19 September 1993	24 October 1993	13 November 1993	14 November 1993	01 June 1993	04 November 1993	30 June 1993
1994	10 March 1994	20 April 1994	14 March 1994	09 September 1994	13 October 1994	03 November 1994	04 November 1994	21 May 1994	23 November 1994	19 June 1994
1995	27 February 1995	09 April 1995	03 March 1995	29 August 1995	02 October 1995	23 October 1995	24 October 1995	11 May 1995	07 November 1995	09 June 1995
1996	17 February 1996	28 March 1996	21 February 1996	16 September 1996	21 October 1996	10 November 1996	11 November 1996	29 April 1996	25 November 1996	28 May 1996
1997	07 March 1997	16 April 1997	09 February 1997	06 September 1997	10 October 1997	30 October 1997	31 October 1997	18 April 1997	14 November 1997	18 May 1997
1998	25 February 1998	05 April 1998	30 January 1998	26 August 1998	30 September 1998	19 October 1998	19 October 1998	08 April 1998	04 November 1998	07 May 1998
1999	14 February 1999	25 March 1999	20 January 1999	13 September 1999	19 October 1999	07 November 1999	08 November 1999	29 March 1999	23 November 1999	27 April 1999
2000	04 March 2000	12 April 2000	28 December 2000	01 September 2000	06 October 2000	26 October 2000	27 October 2000	17 March 2000	11 November 2000	16 April 2000
2001	21 February 2001	02 April 2001	17 December 2001	22 August 2001	25 October 2001	14 November 2001	16 November 2001	06 March 2001	30 November 2001	05 April 2001
2002	12 March 2002	21 April 2002	07 December 2002	10 September 2002	14 October 2002	04 November 2002	05 November 2002	23 February 2002	19 November 2002	25 March 2002
2003	01 March 2003	11 April 2003	26 November 2003	31 August 2003	04 October 2003	25 October 2003	25 October 2003	12 February 2003	08 November 2003	14 March 2003
2004	18 February 2004	30 March 2004	15 November 2004	18 September 2004	21 October 2004	12 November 2004	13 November 2004	02 February 2004	26 November 2004	02 March 2004
2005	08 March 2005	17 April 2005	04 November 2005	07 September 2005	12 October 2005	01 November 2005	02 November 2005	21 January 2005	15 November 2005	20 February 2005
2006	26 February 2006	06 April 2006	25 October 2006	27 August 2006	01 October 2006	21 October 2006	22 October 2006	11 January 2006	05 November 2006	09 February 2006
2007	16 February 2007	27 March 2007	14 October 2007	15 September 2007	20 October 2007	09 November 2007	10 November 2007	21 December 2007	24 November 2007	30 January 2007
2008	06 March 2008	13 April 2008	02 October 2008	03 September 2008	08 October 2008	28 October 2008	29 October 2008	09 December 2008	13 November 2008	19 January 2008
2009	23 February 2009	03 April 2009	21 September 2009	23 August 2009	27 September 2009	17 October 2009	18 October 2009	28 November 2009	02 November 2009	01 January 2008
2010	12 February 2010	24 March 2010	10 September 2010	11 September 2010	16 October 2010	05 November 2010	06 November 2010	17 November 2010	21 November 2010	17 December 2010
2011	02 March 2011	12 April 2011	31 August 2011	01 September 2011	06 October 2011	26 October 2011	27 October 2011	07 November 2011	10 November 2011	06 December 2011
2012	20 February 2012	01 April 2012	20 August 2012	19 September 2012	24 October 2012	13 November 2012	14 November 2012	26 October 2012	28 November 2012	24 November 2012

Table 4: Important National Holidays for Indian exchanges from the period 1990 to 2012

Source: www.bseindia.com and www.nseindia.com

4.3 Data Methodology

The following steps were followed in the present study for the analysis of behavior of the returns of sample indices considered for the study:

i) **STATIONARITY TESTS:** The data of all the nineteen indices were considered for the study. Daily, monthly and yearly closing prices of the nineteen indices as shown in Table 4 above were considered for the study. Before proceeding with further tests, closing prices were tested for stationarity. It was observed that the data considered over specified periods for all the indices were non-stationary in nature. The Augmented Dickey-Fuller test (ADF) on the closing price values was applied to test if the series considered was stationary or not-stationary. Thus, the actual tests were not performed on the daily prices themselves but on the first differences of their natural logarithms as shown below:

$$R_t = \log_e p_t - \log_e p_{t-1}$$

Where R_t represents the return on an index, p_t is the price of the index at the end of the day't', and p_{t-1} is the price of the index at the end of day't-1'.

For the return series R_t, the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i-1}^{p} \beta_i \Delta r_{t-i} + \varepsilon_t$$

Where, $\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t)$

The null hypothesis is H_0: δ=0 to be tested against H_1: δ<1. The acceptance of null hypothesis implies nonstationarity. Thus all the indices were transformed to stationary time series by differencing or by detrending depending upon whether the time series were difference stationary or trend stationary. Since the time series data of all the indices considered were log-differenced and thus stationary in nature, the order of integration (differencing) is one.

ii) **Descriptive Statistics:** Under Descriptive statistics for returns of all indices the following measures like average returns (Mean), Standard Deviation, Median, Minimum and Maximum values, Number of observations, Percentage of positive months, Skewness and Kurtosis, and finally the Jarque-Bera test statistics and its probability were included.[1]

iii) **Comparison of Mean Returns:** Comparison of mean returns for each month/weekday was performed statistically using the difference in mean Test (Ajayi, Mehdian, & Perry 2004; Wong, Hui & Chan 1992). The test statistically compares the mean return of month/weekday/semi-month/turn-of-month to mean return of a consecutive month/weekday/semi-month/rest of months respectively. The hypothesis states that there is no difference between the mean returns of consecutive month/weekday/semi-month/turn-of-month etc.

The hypothesis is stated as follows;

$$H_O : \alpha_i - \alpha_j = 0 \quad against \quad H_1 : \alpha_i - \alpha_j \neq 0$$

Where, for the weekly data, *i*=1(Monday),….., 5(Friday) representing the weekday and *j*=1(Tuesday),….,5(Monday) representing the weekday that is consecutive to *i*. The hypothesis is tested with a difference of means test; where α_i represents the mean return for each weekday (*i*=1(Monday),…5(Friday)), where α_j represents the mean return for each weekday (*i*=1(Tuesday),…5(Monday)), σ_i is the standard deviation of return for each weekday *i* and N is the sample size. DM_j is the t-statistic to test the hypothesis.

$$DM_j = \frac{\alpha_i - \alpha_j}{\sigma_i / \sqrt{N}}$$

For the monthly data, *i*=1(January),….., 12(December) representing the months and *j*=1(February),….,5(January) representing the months that is consecutive to *i*. The hypothesis is tested with a difference of means test; where α_i represents the mean return for each month (*i*=1(January),…5(December)), where α_j represents the mean return for each month (*i*=1(February),…5(January)), σ_i is the standard deviation of return for each month *i* and N is the sample size. DM_j is the t-statistic to test the hypothesis. Similarly difference in means tests were conducted considering other seasonal anomalies.

[1] *Reference: Levin and Rubin, "Statistics for Management", seventh edition*

iv) **Non-Parametric Tests:** Apart from different parametric methods, non-parametric methods were also employed to test seasonality because of their robustness arising from lack of restrictive assumptions such as population normality and homoscedastic variance. Both ***Kruskal-Wallis (H) test***[2] ***and Mann-Whitney U test***[3] were applied to the return series since these are the most scientific and logical non-parametric tests employed across literature for calendar anomalies.

The Kruskal-Wallis Test is employed for testing the equality of mean returns. It requires the entire set of observations to be ranked and then arranged into n_j matrix where n_j represents the rank of the returns and columns represent the month-of-the-year/day-of-the-week/semi-months etc. Statistically, the value of 'H' is calculated as follows: (Levin and Rubin).

$$H = \frac{12}{n(n+1)} \sum \frac{R_J^2}{n_j} - 3(n+1)$$

Where R_j is the sum of ranks of all items in j^{th} column

n_j is the number of cases in the j^{th} column &

N is the sum of observations in all the columns.

Mann-Whitney U Test was also used to test the difference between the mean return of the day exhibiting highest return during the study period and remaining days for the day-of-the-week or for month-of-the-year as a group.

Statistically, the value of 'U' is calculated as follows:

$$U = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - R_1$$

Where n_1 = number of items in study period

n_2 = number of items in remaining days/months group

R_1 = sum of the ranks of the items in study period

R_2 = sum of the ranks of the items in remaining days/months group

[2]is a non-parametric alternative to the one way analysis of variance F-test

[3]Wilcoxon ranked sum test which is essentially identical (though uses different test statistic) to Mann-Whitney U test is also considered in the study. Wilcoxon ranked sum test is also a non-parametric test used alternatively to two-sample t-test. The test is much less sensitive to outliers than the two sample t-test.

v) **Ordinary Least Square (OLS) Regression Model with Dummy Variables:** In order to identify the seasonal patterns in the indices, ordinary least square (OLS) regression with dummy variables was considered for the study (Chan, Anya and Thomas, 1996), which is as follows:

$$R_t = \sum_{i=0}^{h} \alpha_i D_{it} + \varepsilon_t$$

Where R_t = the return on the portfolio at time t;

α_i = the return component attributable to the i^{th} characteristic;

$D_{i,t}$ = the dummy variable taking on the value 1 where the i^{th} observation has the characteristic i and 0 otherwise; and

ε_t = an error term

In regression analysis the dependent variable is frequently influenced not only by ratio scale variables (e.g. income, output, prices, and costs) but also by variables that are essentially qualitative or nominal scale in nature such as color and religion. Dummy variables usually indicate the presence or absence of a "quality" or an attribute by constructing artificial variables that take on values of one or zero. One indicates the presence of that attribute and zero indicates the absence of that attribute. Variables that assume such values are called as dummy variables. Such variables are thus essentially a device to classify data into mutually exclusive categories such as presence or absence of an attribute. In our study, the dummy variables incorporated were exclusively considered as dummy or qualitative in nature. These regression models are also called Analysis of variance (ANOVA) models (Damodar N. Gujurati, 2005). Using the OLS regression model with dummy variables, the model for testing seasonal anomalies such as Month-of the-year effect, Day-of-the-week effect were formalized.

For testing monthly seasonality, the model used is as follows;

$$R_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{June}$$
$$+ \alpha_7 D_{July} + \alpha_8 D_{Aug} + \alpha_9 D_{Sept} + \alpha_{10} D_{oc} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon.$$

The dummy variable takes a value of unity for a given month and a value of zero for all other months. For all t, no separate intercept term was run. In cases where the set of dummy variables was not collinear with an intercept term, a separate intercept term was employed. The intercept terms were specified with dummy variables for all the months except for January month. Thus the omitted month is the benchmark month. The coefficient of each dummy variable measures the incremental effect of that month relative to the benchmark month of January. Thus the existence of monthly seasonal effect will be confirmed if the coefficient of atleast one dummy variable is statistically significant (Pandey, 2002). The intercept term α_1 indicates mean return for the month of January and coefficients α_2 to α_{12} represents the average differences in returns between January and each other month. These coefficients should be equal to zero if the returns for each month is the same and if there is no seasonal effect. ε_t is the white noise error term.

For testing day of the week effect, the model used is as follows;

$$R_t = \alpha_1 + \alpha_2 D_{Tue} + \alpha_3 D_{Wed} + \alpha_4 D_{Thur} + \alpha_5 D_{Fri} + \varepsilon$$

The intercept terms were specified with dummy variables for all the days except for Monday. Thus the omitted day is Monday. The coefficient of each dummy variable measures the incremental effect of that day relative to the benchmark day which is Monday. Thus the existence of day of the week effect will be confirmed if the coefficient of atleast one dummy variable is statistically significant. The intercept term α_1 indicates mean return for Monday and coefficients α_2 to α_5 represents the average differences in returns between Monday and each other days. These coefficients should be equal to zero if the returns for each day is the same and if there is no seasonal effect. ε_t is the white noise error term.

vi) **Holiday Effect:** Ten Holidays were considered for the study from the Stock exchanges calendar for the period 1990 to 2011. Cads by (1992) and Ariel (1990) tested holiday effects confining to pre-holiday and post-holiday periods. For testing the holiday effect, dummy variable was set to one for the three days prior to and three days following the holiday, creating, for a one-day holiday where the market is closed, a window of one week with no observation for the actual day of the holiday. In the event that holiday fell on a Sunday without compensating market closure on the Monday or Friday, the dummy variable window would be the preceding Thursday and Friday and following Monday, Tuesday and Wednesday.[4]

vii) Econometric Approach:

The literature review provides evidence that while examining seasonality in the emerging economies such as India, most studies adopted the methodology similar to the study of the developed stock markets (Keim, 1983; Kato and Schallheim, 1985; Jaffe and Westerfield, 1989). These studies have failed to handle the issues of normality, autocorrelation, heteroscedasticity etc. Thus in order to understand seasonal anomalies, we intend to follow a more robust econometric approach. A combined regression time series model with dummy variables specified with an autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional Heteroscedasticity (GARCH) model is found to be robust to handle the issues of normality, autocorrelation and heteroscedasticity respectively.

In our study, we attempt to test the presence of seasonal anomalies mainly month-of-the-year effect and day-of-the-week effect in both return and volatility equations. From the literature, we know that majority of the studies document seasonal anomalies in only mean returns without considering issues of normality, serial autocorrelation and heteroscedasticity[5]. Thus to overcome all these problems we followed the methods as mentioned below where we will address both autocorrelation and time-varying variance issues and correct for them.

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[4]Lakonishok J. and Smidt S. (1988) found that in examining the day of the week, the last trading day before a holiday and the first trading day after a holiday were excluded to avoid confounding day-of-the-week and holiday effects. We have followed this method in our analysis.

[5]According to literature, using of only OLS methodology in regressing market returns on dummy variables representing various calendar events has two major drawbacks. First, returns in the emerging markets tend to be serially correlated due to market efficiency and the existence of asymmetric information (Bekaert and Harvey,1997), and if autocorrelation is not corrected, this leads to model misspecifications and incorrect inferences (LeBaron, 1992). Secondly, the variance of the error term that OLS assumes to be constant might be in reality time varying or Heteroscedastic.

As mentioned before, in all the studies surveyed in the literature, investigated calendar anomalies using the Standard Ordinary Least Square (OLS) methodology in regressing market returns on dummy variables representing various calendar events which are mainly month-of-the-year effect and day-of-the-week effect in our case. The equation is as follows:

$$R_t = \sum_{i=0}^{h} \alpha_i D_{it} + \varepsilon_t \quad \text{.............................(1)}$$

Where R_t = the return on the portfolio at time t;

α_i = the return component attributable to the i^{th} characteristic;

$D_{i,t}$ = the dummy variable taking on the value 1 where the i^{th} observation has the characteristic *i* and 0 otherwise; and

ε_t = an error term

To eliminate the possibility of having autocorrelated errors, we include the lag values of the return variable to the above equation-1. Thus equation becomes.

$$R_t = \sum_{i=0}^{h} \alpha_i D_{it} + \sum_{i=1}^{p} R_{t-1} + \varepsilon_t \quad \text{.............................(2)}$$

Where, R_t represents returns, D_{it} are dummy variables which get the value of 1 if $i = t$ and zero otherwise with i ϵ (Monday, Tuesday, Wednesday, Thursday, Friday for weekdays and April to March for months). The number of dummies included will have to be the number of trading days minus one (including constant) or number of trading days (excluding constant).[6]

The equation 2 above, assumes the existence of a constant variance, which may result in inefficient estimates, if there is a time varying variance. Therefore, we include the changing variance into estimation. Here we assume that the error term of the return equation has a normal distribution with zero mean and time varying conditional variance of $h_t(\epsilon_t = N(O,h_t))$. Though from the literature, we find various types of modeling of conditional variances, Engle (1982)[7] suggests a model that allows the forecast variance of return equation to vary systematically over time. Here the assumption is that conditional variance, h_t, depends upon the past squared residuals from the return(R_t) equation, $h_t = V_C + \sum_{j=1}^{q} V_j \varepsilon_{t-j}^2$, which is known as Autoregressive Conditional Heteroscedastic (ARCH) Models. Bollerslev (1986)[8] then extended the ARCH process by making h_t a function of lagged values of h_t as well as the lag values of ε_t^2. i.e.,

$h_t = V_C + \sum_{j=1}^{q} V_{Aj} h_{t-j} + \sum_{j=1}^{r} V_{Bj} \varepsilon_{t-j}^2$. This type of modeling is known as GARCH models. Here this specification requires that $\sum_{j=1}^{q} V_{Aj} + \sum_{j=1}^{r} V_{Bj} < 1$ in order to satisfy the non-explosiveness of the conditional variances and that each of $V_{A'}$, $V_{B'}$ and V_C is positive in order to satisfy the non-negativity of conditional variances. Thus the time varying variance model by using a GARCH process would be $h_t = V_C + \sum_{j=1}^{q} V_{Aj} h_{t-j} + \sum_{j=1}^{r} V_{Bj} \varepsilon_{t-j}^2$ where, the volatility is measured by conditional variance.

Thus, we employ Bollerslev's (1986) GARCH (p,q) model as our platform and add to it calendar dummy variables to investigate calendar anomalies on the variance similar to Berument and Kiymaz (2001) and Apollinario*et.al.* (2006). The GARCH (p,q) model assumes that the conditional time-varying variance is both a function of past innovations (ARCH component with order *p*) and past volatility (GARCH component with order *q*). Hence the model would be as follows

$$h_t = V_C + \sum_{j=1}^{q} V_{Aj} h_{t-j} + \sum_{j=1}^{r} V_{Bj} \varepsilon_{t-j}^2 + \delta_{st} D_{st} \quad \text{.................(3)}$$

where, s ϵ(Monday to Friday for weekdays and April to March for months) and $D_{st}$are defined above.

[6] *The reason for this is to avoid the dummy variable trap which gives rise to perfect collinearity among the dummy variables and the constant term (Damodhar N. Gujarati, 2007).*

[7] *Engle, R. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the variance of United Kingdom Inflation." Econometrica, volume 50, pp: 987-1007.*

[8] *Bollerslev, T. 1986. "Generalized Autoregressive Conditional Heteroscedasticity." Journal of Econometrics, volume 31, pp: 307-327.*

The model is estimated using the Quasi-Maximum Likelihood Estimation (QMLE) method introduced by Bollerslev and Wooldridge (1992)[9]. This estimator, however, is inefficient, with degree of inefficiency increasing as departure from normality increases (Engle and Gonzalez-Rivera, 1991). Hence it is imperative to test explicitly the validity of the normality assumption using two tests at the end. The first is Jarque-Bera statistics and the second is the ARCH-LM test[0]. In addition, we test explicitly for the possibility of existence of a risk premium (variance) in the return (mean) equation known as the GARCH-in-Mean model (GARCH-M) test[11].

viii) Model Specification Tests: In order to investigate the validity of time-series models, specifications tests are very crucial. For our study, a 'bottom-up' strategy[12] will be used when performing specification tests.

In other words, bottom-up strategy would involve the following steps;

a. ***Specifying the order of mean equation*** (equation-1), followed by

b. ***Attempting to specify the Auto-Regressive order of the mean equation*** (equation-2). Here autocorrelations in the return series will be examined employing both Auto-Correlation Function (ACF) and the Partial Auto-Correlation Function (PACF). Furthermore, the standard Box-Pierce procedure is also followed. Lastly, Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) values were considered to specify the ARMA order of the mean equation.

In detail, for the study, the residual correlogram, which is a graph that plots series of correlations between residuals against a time interval is used. Using Correlogram and Bartlett bands which represent 95% confidence bounds we will identify statistically significant auto- and partial-correlation lags in order to narrow the search for the optimal ARMA specification. For clarity and easy interpretation of the series under study as white noise, Box-Pierce Q-statistic and Ljung-Box Q-statistic and their p-values were considered. As we know, Box-pierce Q-statistic and Ljung-Box Q-statistic and their p-values are usually considered under the null hypothesis of white noise for the number of terms in the sum that underlies the Q-statistic.

Box-Pierce Q-statistic is approximately distributed as a χ^2_m random variable under the null hypothesis that y is white noise i.e.

$$Q_{BP} = T\sum_{\tau=1}^{m}\hat{\rho}^2(\tau)$$

A slight modification of Box-Pierce Q-statistic which is designed more closely to follow the χ^2 distribution in small samples is Ljung-Box Q-statistic, which is also distributed approximately as χ^2_m random variable, under the null hypothesis that variable considered is a white noise. The Ljung-Box Q-statistic is represented as follows:

$$Q_{LB} = T(T+2)\sum_{\tau=1}^{m}\left(\frac{1}{T-\tau}\right)\hat{\rho}^2(\tau)$$

Ljung-Box Q-statistic is same as the Box-pierce Q-statistic except that sum of squared autocorrelations is replaced by a weighted sum of squared autocorrelations, where the weights are (T+2)/ (T-τ).

After executing various ARMA specifications, the model with the lowest Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) values were considered. The AIC and SIC are goodness of fit measures- the lower the value, the better the model is at accounting for the variation in the data. Adding additional lags to the model

[9]The advantage of this method is that even in case where the residuals are not conditionally normally distributed, the ARCH parameter estimates and the covariance matrix are still consistent given that the conditional mean and the conditional variance are correctly specified.

[10]The GARCH-LM test is a Lagrange Multiplier test to examine whether the standardized residuals exhibit additional ARCH effects.

[11]Engle et.al, 1987.

[12]Following Tooma and Sourial (2004) and recommendations of Wooldridge(1991), Hagerud (1997) , Kamaly A. and Tooma A.E. (2009)

will only reduce the value of the criteria only if the fall in the residual sum of squares outweighs the penalty for the loss of degrees of freedom from adding additional parameters.

The Akaike Information Criteria (AIC) is effectively an estimate of the out-of-sample forecast error variance, but it penalizes degrees of freedom more harshly. It is used to select among various ARMA models.

$$AIC = e^{\left(\frac{2k}{T}\right)} \frac{\sum_{t=1}^{T} e_t^2}{T}$$

where, k is the degrees of freedom used in model fitting.

The Schwarz Information Criteria (SIC) is an alternative to the AIC but penalizes degrees of freedom more harshly than AIC.

$$AIC = T^{\left(\frac{k}{T}\right)} \frac{\sum_{t=1}^{T} e_t^2}{T}$$

Thus optimal Auto-Regressive order of the mean equation would be found out by considering AIC and SIC values but, in case of disagreement between AIC and SIC values, SIC values would be given preference as it penalizes degrees of freedom more harshly than AIC[13].

c. ***Testing for the conditional variance equation and testing the validity of normality assumption.***

   As discussed above, two tests will be conducted. The first is Jarque-Bera statistics and the second is the ARCH-LM test.

d. Lastly, ***we test explicitly for the possibility of existence of a risk premium (variance)*** in the return (mean) equation known as the GARCH-in-Mean model (GARCH-M) test.

[13]*Cosimano and Jansen (1988) argue that the presence of the autocorrelation in the residual terms may misleadingly indicate the presence of the ARCH effect. Hence, to the OLS regression analysis, sufficient numbers of lags are included in order to avoid the auto-correlated errors.*

4.4 Limitations of the Study

The following are some of the limitations of the present study which are as follows;

a) The present study is restricted to only Indian stock markets;

b) It considers indices belonging to two major stock exchanges namely BSE and NSE stock exchange respectively;

c) It is based mainly on secondary data; and

d) The present study considers only nineteen indices listed on both BSE and NSE stock exchanges due to lack of data availability. The index for which the data availability was less than three years was ignored from the study.

5.0 Findings of the Study

The research mainly aimed at understanding;

i. Whether the selected indices confirm the existence of a certain anomaly?

The studies found presence of all major calendar anomalies in the Indian stock markets.

With respect to Day-of-the-week effect, high positive returns were observed on Wednesday and Monday for broader indices and sectoral indices respectively. The largest mean returns was observed on Monday especially for sectoral indices (when compared to higher returns of Friday and lowest returns on Monday as observed in developed countries) which point towards lagging effect of Indian sectors taking cues from the global markets. The results confirm towards “wait and watch principle” followed by investors. These high returns towards the beginning of the week followed by lowest returns on Tuesday is in contrast to the evidence obtained from other markets.

Considering Month-of-the-Year effect, from the analysis we can notice that, the mean monthly returns are significantly different from zero mainly in the Months of January, February, and December. The higher Positive December mean returns followed by negative returns in the months of January and February could be caused by a change in investor’s behavior, anticipating January effect and March effect in Indian stock markets and other stock markets since the fiscal year in India starts in April and ends in March, whereas it is January to December in other developed countries. Furthermore, a closer look at the sub-period values reveals that, December month is statistically significant in recent period i.e., 2002-2011. The significant February effect observed in Indian markets in the first sub-periods seems to have changed. Thus from the analysis, we can conclude that though tax loss hypothesis helps explain monthly effect in Indian stock markets for a brief period, but all the indices indicate a disappearing March/April effect over the whole sample period. Even after considering the time-varying volatility, the results reconfirm the OLS regression results. December is found to be very significant in all the broader indices except for BSE Sensex index wherein January is observed to be significant. Whereas in case of sectoral indices, December was observed to be significant for all the indices except for BSE FMCG, BSE Teck, BSE O & Gand CNX INFRA Indices respectively. Thus the results obtained indicated higher integration of Indian markets than ever in the recent period.

In the order of the occurrence of Holidays on weekdays, Wednesday and Friday are observed to be the days highly likely to have holidays than rest of the other days. If we sub-divide the calendar year based on occurrence of holidays, important holidays such as Ganesh Chaturthi, Dussehra, Diwali and Bakrid occur mainly during the later part of the calendar year i.e. between September and December. Especially, these holidays seem to occur mainly in the second half of the month. Similarly, other holidays namely Mohurram, Maha Shivaratri and Rama Navami usually occur during January and April months. Considering these holidays, the percentage of occurrence of holidays on Tuesday is found to be highest (27%) followed by Wednesday (20%). The holidays namely Maha Shivaratri, Rama Navami, Ramzan are observed to occur towards the first half of the calendar month during the entire study period. Thus, there is very likely chance that holiday effect is the reason for semi-month effect and Wednesday effect as the behavior of Wednesday return behavior is found to be dissimilar to security returns around holidays (Ariel, 1990).

Lastly, considering the Turn-of-the-month effect, when compared to sectoral indices, broader indices seem to reveal anomaly among daily returns towards the turn-of-the-month. The sectoral indices have minor or no indication for turn-of-the-month effect, while broader indices especially mid-cap and small-cap indices seem to show significant turn-of-the-month effect. Thus, turn-of-the-month effect seems to be mostly present in the broader indices.

ii. If anomalies exist, whether these anomalies are stable and consistent over time and across indices considered i.e., are they true anomalies?

Considering the results of the econometric analysis, we observe disappearing pattern of major anomalies. These anomalies observed showed consistency with the existing literature on Indian sector.

6.0 Observations, Suggestions & Conclusions

6.1 Observations And Suggestions

The following are some of the important revelations' of the study;

- **a.** Integration of the markets is observed to be happening at a rapid pace and trading strategies adopted have to consistently revised and retested as returns are observed to be not stable and consistent over the entire study period and sub-periods. Thus investors should be aware of the changing environment in the financial markets throughout the world.
- **b.** Day-of-the-week effect was observed to be present in the Indian capital markets.
- **c.** It is found true that the, investments are observed to be high on Mondays causing Monday effect in the pre-rolling settlement period, and after the introduction of rolling settlement, Monday effect is insignificant. In the recent times after 2002, Wednesdays have highest returns and Tuesday has the lowest returns in majority of the indices.
- **d.** The higher proportion of announcements after the close of trading on Friday than on any other day of the week (Patell and Wolfson, 1982) and the pattern of trade by FIIs in India matching with

the occurrence of pattern of day anomalies might give us clues on occurrence of day-of-the-week effect in India stock market. Thus, lower Tuesdays returns followed by higher Wednesday returns in Indian stock markets point towards markets taking more time to absorb the news announcements and decisions by companies, policy makers and institutional investors throughout the world.

e. FIIs play a very significant role in ensuring momentum of the Indian capital markets and thus a constant vigilance by regulators with respect to the investment patterns/trading strategies adopted by FIIs and its relevance with calendar anomalies can help regulators in ensuring disappearance of day anomalies in Indian stock market.

f. The analysis finds semi-month effect and turn-of-the-month effect to be present in Indian stock markets.

g. Holiday effect is observed in the Indian stock market. The mean returns around holidays namely Ganesh Chaturthi, Dussehra, Bakrid and Mohurram are significantly lower when compared to other days.

h. Month-of-the-year effect is observed in the Indian stock markets. The results show patterns changing in the recent periods. Tax-loss hypothesis though helps in explaining February effect in the first sub-period (1991-2001), the theory is insignificant as we observe patterns changing in the recent time periods. We infer month-of-the-year effect aligning with the effects seen globally. December effect is observed in the recent period and a trading strategy of buying in the month of January and February and selling in the month of April and August (for short term gain) or November and December months (for long term gain) would be profitable to the investors in case of majority of the indices.

i. The results obtained from the study can be used in forming various trading strategies by the retail, Institutional and non-Institutional investors to make abnormal profits. The study also finds higher risk during these periods and hence is advisable to form trading strategies knowing the risks associated with it.

j. We observed that, calendar anomalies exist in both broad and sectoral indices respectively. The study also found non-linearity between risk and returns, which is contrary to the capital market theory in terms of higher returns considering lower risks for the portfolio's. Thus, the market regulators can take appropriate steps to stabilize the market by taking some corrective steps and adopting various regulatory measures.

k. The study found changes in the pattern of the anomalies over various sub-periods in case of all the five anomalies considered for the study. This encourages us to believe that the appropriate regulatory measures taken by the regulators over the years have been successful to control these anomalous behaviors in the capital markets, which inturn has helped protect the interest of the investors.

l. The global integration of the domestic markets, more so in the recent years reinforces regulators to recommend and impose still tougher rules and regulations to ensure transparency in reporting information by the companies and also in reporting transactions done by the foreign and domestic investors in the future such as mutual funds.

6.2 Conclusions

The study examined the Indian stock market, to determine whether the empirical anomalies of seasonality detected in the U.S. market and other international market is also present in India. In the study, we observe that the Indian stock market presents different patterns in stock returns and the study brings forth distinct conclusions to prove the validity of several popular beliefs regarding calendar anomalies across various sub-periods. It is observed that the strategies to make profits may lose ground very quickly with global economies changed outlook to liberalization, political stability, increased foreign trade and commerce, and rise of multinational companies. The study finds that the markets may be fast converging to a point where opportunities will become faint, especially after 2002. With Advanced trading systems put in place and markets seamlessly integrated by operating

24 hours in different time zones across the world, markets seem to become efficient with India being more in sync with the global markets now than ever. The study provides conclusive results to the presence of calendar anomalies, but, at the same time, points finger towards the extent of influence the stock markets throughout the world has had on Indian counterpart which appears slow in the initial periods but very fast in the recent times mainly after 2002.

Considering the results obtained for all the calendar anomalies, one can find the results indicating towards a 360 degree causal relationship. There seems to appear a causal impression of one calendar anomaly on the other i.e., there appears to be interlinking of one calendar anomaly results on the other anomaly more so in the recent times. The studies done before concentrated on explaining the anomalies completely independently which might have been the rationale for not arriving at any conclusive evidence on explaining the cause of these anomalies.

Thus it can be concluded that, the results observed indicates the presence of significant calendar anomalies which also seem to be associated with releases of information, and the indices act as proxy for differentials in the speed with which companies release information to the market, and anomalies are displayed due to inadequate adjustment of prices to available information. Calendar anomalies exist in Indian stock markets, but, the calendar anomalies seem to get converged with the patterns observed across major global economies which might be the result of integration of the markets. Holiday effect can be considered as a key calendar anomaly in explanation of other calendar anomalies mainly day-of-the-week effect, Month-of-the-year effect and semi-month effect. With Indian capital markets striving to achieve global standards, calendar anomalies would be just a reflection of markets to the global clues and information and would thus provide no opportunities to the investors to make abnormal profits. The convergence of the patterns also points towards higher integration and less insulation of the Indian markets today than in the earlier time periods. The Indian stock markets seem to be more sensitive to the movements and clues provided by the global stock exchanges. Hence, though the markets are considered inefficient, they are slowly moving towards integration and thus efficiency. Indian market can be considered as the best example of this phenomenon.