Macrothink Institute™

Asian Journal of Finance & Accounting
ISSN 1946-052X
2011, Vol. 3, No. 1: E11

Seasonality and Market Crashes in Indian Stock Markets

Mihir Dash[1]

School of Business, Alliance University

Anirban Dutta

Genpact India Pvt. Ltd.

Mohit Sabharwal

Adani Wilmar Ltd.

Received: September 28, 2011 Accepted: November 20, 2011 Published: December 1, 2011

doi:10.5296/ajfa.v3i1.997 URL: http://dx.doi.org/10.5296/ajfa.v3i1.997

Abstract

The presence of seasonal effects in monthly returns has been reported in several developed and emerging stock markets. The objective of this study is to explore the interplay between the month-of-the-year effect and market crash effects on monthly returns in Indian stock markets. The study uses dummy variable multiple linear regression to assess the seasonality of stock market returns and the impact of market crashes on the same. The results of the study provide evidence for a month-of-the-year effect in Indian stock markets, particularly positive November, August, and December effects, and a negative March effect. Further, the study suggests that the incidence of market crashes reduces the seasonal effects.

Keywords: seasonality, stock market returns, month-of-the-year effect, market crash effects, dummy variable regression.

JEL Classification: G14

[1] School of Business, Alliance University, Chikkahagade Cross, Chandapura-Anekal Main Road, Anekal, Bangalore-562106, tel: +91-9945182465, email: mihirda@rediffmail.com

Introduction

The Efficient Market Hypothesis (EMH) asserts that in informationally-efficient markets, the market prices of assets should be equal to their true expected values, reflecting all information available to the market participants (Fama, 1965; Fama et al, 1969). In particular, this would imply that stock returns follow a random walk, unpredictable, without pattern.

However, several market anomalies, contradicting the EMH, have been reported, such as the January effect, the Monday effect, the turn-of-the-month effect, the holiday effect, the small-firm effect, announcement effects, and many others. Such market anomalies are primarily due to behavioural causes (Schwert, 2003). The presence of market anomalies seems to be ubiquitous, occurring in stock markets around the world, in both developed markets and emerging markets.

For example, the January effect is the phenomenon in which asset prices tend to increase in the month of January; in fact, between the last trading day in December of the previous year and the fifth trading day of the new year in January. A theory explaining the January effect is that of tax-loss selling, wherein investors sell their losing positions at the end of December; these stocks are sold typically at a discount to their market value, and they are subsequently picked up by speculators, creating a buying pressure in the market (Rozeff and Kinney, 1976, Kiem, 1983). In fact, it is reported that when the S&P500 has a net positive gain in the first five trading days of the year, there is about an 86% chance that the stock market will rise for the year, while when the first five days of January yield a net loss, there is no statistical bias of the market, up or down[2].

Literature Review

There is an extensive literature documenting several forms of market anomaly, especially in the matured capital markets such as those in US and Europe. In particular, the calendar anomalies such as the month-of-the-year and day-of-the-week effects have been comprehensively studied in matured as well as emerging stock markets. The following undertakes a review of some of the prominent literature on seasonality in stock returns.

The pioneering work on seasonality was by Watchel (1942), who was the first to report seasonality in stock returns. Rozeff and Kinney (1976) studied the January effect in New York Exchange stocks, finding that average return for the month of January was higher than other months. Keim (1983) studied the January effect, along with size effects in stock returns. He found that January returns of small firms were significantly higher than large firms, providing evidence for the tax-loss-selling hypothesis. Similar effects were found by Reinganum (1983) and by Gultekin and Gultekin (1983). Brown et al. (1985) found evidence of December-January and July-August seasonal effects in the Australian stock market, with the latter due to a June-July tax year. On the other hand, Raj and Thurston (1994) found that the January and April effects in the New Zealand stock market were not statistically significant. Mill and Coutts (1995) found calendar effects in British stock markets. Choudhary (2001) found the January effect on the UK and US stock markets, but not in the German stock market.

---
[2] http://www.mysmp.com/stocks/january-effect.html

Fountas and Segredakis (2002) studied seasonal patterns in returns in several markets around the world. The main reasons they attributed for the January effect in stock returns in most of the developed stock markets were the tax loss selling hypothesis, settlement procedures, and insider trading information. Another explanation for seasonal effects is window-dressing 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 December and buy them back after the reporting date in January in order to hold their desired portfolio structure again.

Another interesting effect is the holiday effect, in which higher returns are exhibited around holidays, mainly in the pre-holiday period as compared to returns of the normal trading days. Several studies examine this effect (Lakonishok and Smidt, 1988; Ariel, 1990; Cadsby and Ratner, 1992). Husain (1998) studied the Ramdhan effect in the Pakistan stock market, finding a significant decline in stock returns volatility in the month of Ramdhan, though no significant change in the mean returns.

The day-of-the-week effect in stock market returns has also been extensively reported in developed and emerging stock markets, with lower mean returns on Mondays and higher mean returns on Fridays (Kelly, 1930; Hirsch, 1968; Cross, 1973; Gibbons and Hess, 1981; Smirlock and Starks, 1986; Jaffe and Westerfield, 1989).

Several studies have also examined seasonality of stock returns in Indian stock markets. Pandey (2002) examined seasonality in monthly returns of the BSE Sensex, finding evidence of the January effect. Bodla and Jindal (2006) also found evidence of seasonality in both Indian and US markets. Kumari and Mahendra (2006) studied the day-of-the-week effect in the BSE and the NSE, finding negative returns on Tuesday and relatively higher returns on Monday. Sah (2008) studied seasonality in S&P CNX Nifty, investigating both the day-of-the-week effect and the month-of-the-year effect, finding evidence for a Friday effect and monthly anomalies for July, September, December, and January. Elango and Al Macki (2008) studied the day-of-the-week effect in the NSE, finding evidence of the Monday effect, with lowest daily returns on Monday, and with highest daily returns on Wednesday. On the other hand, Elango and Pandey (2008) studied the month-of-the-year effect in the NSE, finding the presence of a January anomaly, with March and April having significant negative returns, and November and December showing significant positive returns. Patel (2008) also studied calendar effects in monthly returns in Indian stock markets, finding two distinct effects: a November-December effect, in which the mean returns for November and December were significantly higher than those in the other ten months, and a March-to-May effect, in which mean returns for the months March to May were significantly lower than those during the other nine months; and they showed that these effects were independent of each other.

The literature has highlighted some widely-accepted market anomalies in both developed and emerging markets, though with some differences in different time periods and in different markets. There is, however, a gap in the literature regarding the impact of market crashes on market anomalies, particularly calendar effects. Most studies tend to regard market crashes as aberrations or outliers, and remove them from consideration when investigating market anomalies. The present study examines the interplay between market crashes and the month-of-the-year effect in Indian stock markets.

Data and Methodology

The present study focuses on the monthly patterns of returns in the Indian stock market, specifically the Bombay Stock Exchange (BSE). To avoid distortions due to size effects, it is appropriate to use a value-weighted index to detect the seasonal effect in stock returns. BSE's Sensitivity Index (Sensex) is such a value-weighted share price index, including the thirty most actively traded shares on the BSE, weighted by their market capitalizations (Pandey, 2002). The study uses historical data covering the post-reform period, leading up to the global financial crisis in the third quarter of 2007.

The data used for the study were the monthly closing Sensex values in the period April 1999 to March 2007, collected from the BSE website[3]. Monthly returns were calculated as the continuously compounded monthly percentage change in the closing Sensex values, using the formula: $R_t = \ln(P_t/P_{t-1})$, where R_t represents the monthly returns in period t, and P_t represents monthly closing Sensex value for period t. The market crashes considered for the study were as follows: Apr'00, Jul'00, Oct'00, Mar'01, Sep'01, May'04, Oct'05, May'06, and Feb'07.

The study tests for seasonality and market crash effects using dummy variable regression. Monthly returns are taken as the dependent variable, and dummy variables for each month and each market crash are taken as the independent variables; i.e. $R_t = \alpha + \sum_{i=1}^{12} \beta_i M_i + \sum_{j=1}^{k} \gamma_j C_j + \epsilon_t$, where the M_i represent the dummy variables for each month, while the C_j represent the dummy variables for each market crash. The significance of the coefficients β_i and γ_j in the regression indicate significance of the monthly effects and the crash effects, respectively.

In order to avoid the problem of spurious regression, the Sensex returns series has to be tested for stationarity. This is done using the augmented Dickey-Fuller (ADF) test for unit roots, which involves regressing the first difference of the series against a constant term, a time trend, the series lagged one period, and the differenced series at n lag lengths (Elliot et al, 1996); symbolically: $\Delta R_t = \alpha + \beta t + \gamma R_{t-1} + \sum_{i=1}^{m} \Delta R_{t-i} + \epsilon_t$. If the coefficient γ is statistically significantly and negative, then the hypothesis that R_t is nonstationary (specifically, having a unit root) is rejected. The ADF test can be carried out with and/or without the constant and/or trend; one has to choose the appropriate lag length m.

Analysis and Findings

As a preliminary analysis, ANOVA was performed to test for differences in mean monthly

[3] www.bseindia.com

returns between different months. The results are presented in Table 1 below.

Table 1. ANOVA test for differences in mean monthly returns between different months

descriptive statistics for monthly return

Month	Mean	Std. Dev.
January	1.8127%	4.13377%
February	1.1003%	4.89012%
March	-3.7858%	7.31299%
April	-1.9988%	4.56146%
May	-0.8500%	12.07133%
June	4.0319%	5.13898%
July	0.8260%	7.45880%
August	4.7709%	4.55991%
September	-0.4850%	8.84573%
October	-0.7107%	7.28869%
November	7.3026%	2.91993%
December	4.8462%	5.19512%
Overall	**1.4408%**	**7.01023%**
F-stat	**1.8900**	
p-value	**0.0520**	

(source: primary data)

Duncan's post hoc test

Month	Subset for alpha = .05		
	Subset 1	**Subset 2**	**Subset 3**
March	-3.7858%		
April	-1.9988%	-1.9988%	
May	-0.8500%	-0.8500%	
October	-0.7107%	-0.7107%	
September	-0.4850%	-0.4850%	
July	0.8260%	0.8260%	0.8260%
February	1.1003%	1.1003%	1.1003%
January	1.8127%	1.8127%	1.8127%
June	4.0319%	4.0319%	4.0319%
August		4.7709%	4.7709%
December		4.8462%	4.8462%
November			7.3026%
p-value	**0.0500**	**0.0900**	**0.0990**

(source: primary data)

The ANOVA was found to be not significant, implying that there was no significant difference in mean monthly returns between different months, i.e. no seasonal effect. However, Duncan's post hoc test indicated that March returns were significantly lower than those of November, December, and August; and that November returns were significantly higher than those of March, April, May, October, and September. Thus, there was found to be evidence of seasonality in monthly returns.

To test for the presence of a unit root, the augmented Dickey-Fuller test was performed. The results are presented in Table 2 below.

Table 2. augmented Dickey-Fuller test

	ADF regression
Constant	-2.1830 (0.2250)
Trend	0.0670 (0.0600)
R_{t-1}	-1.0660 (0.0010)**
ΔR_{t-1}	0.0800 (0.7780)
ΔR_{t-2}	0.1020 (0.6820)
ΔR_{t-3}	0.0620 (0.7700)
ΔR_{t-4}	-0.0410 (0.8220)
ΔR_{t-5}	-0.1370 (0.3610)
ΔR_{t-6}	-0.0140 (0.8970)
Statistics:	
R^2	51.20%
F_{cal}	10.3530
p-value	0.0000**

(source: primary data)

The results of the ADF test showed a significant negative coefficient of R_{t-1}, indicating rejection of the hypothesis of a unit root, so that the monthly returns series can be taken to be stationary.

The regression analysis of monthly returns was performed subsequently. Regression with trend only yielded insignificant results (R^2 = 1.60%, F_{cal} = 1.4940, p-value = 0.2250). The results of the three dummy variable regressions performed are presented in Table 3 below.

Table 3. dummy variable regression of monthly returns

	Model I: *Trend + Seasonality*	**Model II:** *Trend+ Crashes*	**Model III:** *Trend + Seasonality + Crashes*
Constant	-5.5950 (0.0205)*	1.2310 (0.1625)	-4.5640 (0.0290)*
Trend	0.0340 (0.0880)	0.0330 (0.0705)	0.0450 (0.0210)*
January	5.6670 (0.0460)*		4.0790 (0.0720)
February	4.9200 (0.0710)		4.9680 (0.0435)*
April	1.9580 (0.2850)		0.9860 (0.3705)
May	3.2770 (0.1640)		7.2630 (0.0.095)**
June	8.1250 (0.0085)**		6.6130 (0.0100)*
July	4.8850 (0.0730)		4.7720 (0.0490)*
August	8.7960 (0.0050)**		7.2620 (0.0550)*
September	3.5060 (0.1470)		3.8240 (0.0925)
October	3.2460 (0.1655)		4.5740 (0.0645)
November	11.2250 (0.0005)**		9.6590 (0.0005)**
December	8.7340 (0.0050)**		7.1570 (0.0060)**
2000_Crash$_1$		-8.7520 (0.0650)	-4.0820 (0.2430)
2000_Crash$_2$		-12.1280 (0.0185)*	-11.2810 (0.0270)*
2000_Crash$_3$		-11.5850 (0.0230)*	-10.5540 (0.0365)*
2001_Crash$_1$		-18.4060 (0.0010)**	-12.8790 (0.0140)*
2001_Crash$_2$		-16.5340 (0.0025)**	-14.9010 (0.0055)**
2004_Crash		-20.5070 (0.0005)**	-22.6870 (0.0000)**
2005_Crash		-12.8240 (0.0135)*	-12.5120 (0.0170)*
2006_Crash		-18.7480 (0.0010)**	-21.2070 (0.0005)**
2007_Crash		-12.9060 (0.0135)*	-13.1750 (0.0130)*
Statistics:			
R^2	21.80%	42.50%	55.00%
SSE	3612.0690	2658.3380	2078.5340
df_{SSE}	82	84	73
F_{cal}	1.9060	6.1970	4.2500
p-value	0.0450*	0.0000**	0.0000**

(source: primary data)

Due to multicollinearity of the month dummy variables, the March dummy variable was not entered into the models. Thus, March can be viewed as the base month, with the constant term representing March returns, and the regression coefficients representing monthly differences from March returns.

Model I shows the results of the dummy variable regression of monthly returns on the trend and month dummy variables taking March as the base. The regression was found to be statistically significant, explaining 21.80% of the overall variation in monthly returns. In this model, the trend was found to be statistically insignificant; amongst the months, November, August, December, July, and January were found to have significant positive returns, while March (represented by the constant term) was found to have significant negative returns. This more or less corresponds with the results obtained from Duncan's post hoc test.

Model II shows the results of the dummy variable regression of monthly returns on the trend and market crash variables. The regression was found to be statistically significant, explaining 42.50% of the overall variation in monthly returns. In this model, the constant term and the trend were both found to be statistically insignificant, while all of the market crashes were found to be highly significant, except for the Apr'00 crash. Obviously, all of the crashes had a negative effect on monthly returns, the worst being the May'04 crash, followed by the May'06 crash, the Mar'01 crash, the Sep'01 crash, the Feb'07 crash, the Oct'05 crash, the Jul'00 crash, the Oct'00 crash, and finally the Apr'00 crash.

Model III shows the results of the dummy variable regression of monthly returns on the trend, month, and market crash variables. The regression was found to be statistically significant, explaining 55.00% of the overall variation in monthly returns. In this model, the trend was found to statistically significant; amongst the months, November, May, August, December, June, February, and July were found to have significant positive returns, while March (represented by the constant term) was found to have significant negative return; while all of the market crashes were found to be highly significant, except for the Apr'00 crash. Again, all of the crashes had a negative effect on monthly returns, the worst being the May'04 crash, followed by the May'06 crash, the Sep'01 crash, the Feb'07 crash, the Mar'01 crash, the Oct'05 crash, the Jul'00 crash, the Oct'00 crash, and finally the Apr'00 crash. Also, the month effects were found to be reduced by the inclusion of market crashes, except for February, May, September, and October; and the impact of the market crashes were found to be reduced by the inclusion of month effects, except for the May'04 crash, the May'06 crash, and the Feb'07 crash.

The relative significance of group effects was assessed by comparing the results of model III with model II and model I, in turn. The results are presented in Table 4 below.

Table 4. test for significance of group effects

variable group	F_{cal}	p-value
month-of-the-year effect	1.8512	0.0606
crash effect	5.9843	0.0000**

(source: primary data)

It was found that the combined month effects were not statistically significant in the presence of crash effects, while the combined crash effects were highly statistically significant in the presence of month effects.

Conclusions

The results of the study provide evidence for a month-of-the-year effect in Indian stock markets. In particular, there is clear indication of positive November, August, and December effects, and a negative March effect. These results are consistent with the literature, particularly Patel (2008). The end-of-the-year effect (i.e. positive November and December effects) could be a Diwali effect, with a huge surge in the purchase of household goods, electronic equipments, and gold in India, usually in November. Another possible contributing factor could be the Rabi harvest (also called the "winter crop"), which affects commodity prices and, in turn, stock market prices. Similarly, the Kharif harvest (also called the "monsoon crop") could be a contributing factor for the August effect.

The results of the study also indicate a highly significant negative impact of market crashes on stock market returns, as would be expected, and that the incidence of market crashes reduces the seasonal effects. There is scope for further investigation of the interplay between market crashes and seasonality, perhaps studying mediating/moderating effects.

The results of the study also provide evidence for a March effect for stock returns in India. This could be because the Indian tax year ends in March, in contrast with the US tax year which ends in December. The negative March returns could be because of "tax-loss selling."

There are some limitations inherent in the study. The choice of the market crashes to include in the analysis may have a bearing on the results. The results of the study could also be affected by the choice of the research period, as the selected research period is generally considered to be a bull period. Particularly, the research period excludes the global financial crisis; further analysis including the global financial crisis and its aftermath would provide a much better insight into the same. There is thus great scope for extending the study.

References:

Ariel, R.A. (1990). High Stock Returns before Holidays: Existence and Evidence on Possible Causes. *Journal of Finance,* 45, 1611–25. http://dx.doi.org/10.2307/2328753

Bodla, B.S., & Jindal, K. (2006). *Seasonal Anomalies in Stock Returns: Evidence from India and the US. Decision*, 33(1), 46-55.

Brown, P., Keim, D.B., Keleidon, A.W., & Marsh, T.A. (1983). Stock Return Seasonalities and the Tax-Loss-Selling-Hypothesis: Analysis of the Arguments and Australian Evidence. *Journal of Financial Economics,* 12, 105-127. http://dx.doi.org/10.1016/0304-405X(83)90030-2

Cadsby, C.B., & Ratner, M. (1992). Turn-of-the-Month and Pre-Holiday Effects in Stock Returns. *Journal of Banking and Finance,* 16, 497–509. http://dx.doi.org/10.1016/0378-4266(92)90041-W

Choudhary, T. (2001). Month of the Year Effect and January Effect in pre-WWI stock returns: Evidence from a non-linear GARCH. *International Journal of Finance & Economics,* 6, 1-11. http://dx.doi.org/10.1002/ijfe.142

Cross, F. (1973). The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*, Nov.–Dec. 1973, 67–69. http://dx.doi.org/10.2469/faj.v29.n6.67

Elango, R., & Al Macki, N.M. (2008). Monday Effect and Stock Return Seasonality: Further Empirical Evidence. *The Business Review*, Cambridge 10(2), 282-288; available at SSRN: http://ssrn.com/abstract=1103627

Elango, R., & Pandey, D. (2008). An Empirical Study on January Anomaly and Return Predictability in an Emerging Market: Evidence from India; available at SSRN: http://ssrn.com/abstract=1150080

Elliott, G., Rothenberg, T. J., & Stock, J.H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica,* 64(4), 813–836. http://dx.doi.org/10.2307/2171846

Fama, E. F. (1965). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Business,* 1, 34-105. http://dx.doi.org/10.1086/294743

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review,* 10(2), 1-21. http://dx.doi.org/10.2307/2525569

Fountas, S., & Segredakis, K.N. (2002). Emerging stock markets return seasonalities: the January effect and the tax-loss selling hypothesis. *Applied Financial Economics,* 12, 291-299.

http://dx.doi.org/10.1080/09603100010000839

Gibbons, M.R., & Hess, P., (1981). Day-of-the-Week Effects and Asset Returns. *Journal of Business,* 54, 579–96. http://dx.doi.org/10.1086/296147

Gultekin, M.N., & Gultekin, N.B. (1983). Stock Market Seasonality: International Evidence. *Journal of Financial Economics,* 12, 469-481. http://dx.doi.org/10.1016/0304-405X(83)90044-2

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

Husain, F. (1998). A Seasonality in the Pakistani Equity Market: The Ramdhan Effect. *The Pakistan Development Review,* 37(1), 77-81

Jaffe, J.F., Westerfield, R., & Christopher, M. (1989). A Twist on the Monday Effect in Stock Prices: Evidence from the U.S. and Foreign Stock Markets. *Journal of Banking and Finance,* 13, 641-650. http://dx.doi.org/10.1016/0378-4266(89)90035-6

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

Keim, D.B. (1983). Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics,* 12(1), 13-32, http://dx.doi.org/10.1016/0304-405X(83)90025-9

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,* 25(1), 75-97. http://dx.doi.org/10.1016/0304-405X(89)90097-4

Kumari, D., & Mahendra, R. (2006). Day-of-the-week and other market anomalies in the Indian stock market. *International Journal of Emerging Markets,* 1(3), 235-246.

http://dx.doi.org/10.1108/17468800610674462

Lakonishok, J., & Smidt, S. (1988). Are seasonal Anomalies real? A ninety years perspective. *The Review of Financial Studies,* 1(4), 403-425. http://dx.doi.org/10.1093/rfs/1.4.403

Mills, T.C., & Coutts, J.A. (1995). Calendar Effects in the London Stock Exchange FTSE Indices. *European Journal of Finance,* 1, 79-93. http://dx.doi.org/10.1080/13518479500000010

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

Patel, J.B. (2008). Calendar Effects in the Indian Stock Market. *International Business and Economic Research Journal*, 7(3), 61-69.

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,* 1, 81-93. http://dx.doi.org/10.1080/135048594358195

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*, 12, 89-104. http://dx.doi.org/10.1016/0304-405X(83)90029-6

Rozeff, M.S., & Kinney, W.R. (1976). Capital Market Seasonality: The Case of Stock Market Returns. *Journal of Financial Economics,* 3, 376-402. http://dx.doi.org/10.1016/0304-405X(76)90028-3

Sah, A.N. (2008). Stock Market Seasonality: A Study of the Indian Stock Market. NSE Research Paper, available at NSE: www.nseindia.com/content/research/res_paper_final228.pdf

Schwert, G.W. (2003). Anomalies and Market Efficiency; in *Handbook of the Economics of Finance*, Edited by Constantinides, G.M., Harris, M., Stulz, R., Publ. Elsevier Science B.V

Smirlock, M., & Starks, L. (1986). Day of the Week and Intraday Effects in Stock Returns. *Journal of Financial Economics,* 17, 197-210. http://dx.doi.org/10.1016/0304-405X(86)90011-5

Wachtel, S.B. (1942). Certain Observations on Seasonal Movement in Stock Prices. *Journal of Business,* 15 (2), 184-193.