Does seasonality persists in Indian stock markets?

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Abstract

The 'conventional wisdom' about efficient markets is that there are little excess returns, relative to the market returns (and the level of risk) that one can make by analysing historical data. But researchers have gathered systematic evidence about markets violating this conventional wisdom. Some of these are calender effects, small-firm or size effect etc. This paper examines a calender effect known as 'the-month-of-the-year-effect' and examine whether this much-hyped anomaly is a persisting feature in the Indian market. The paper shows that the previous evidence on seasonality could be the result of the very nature of parametric methods, that it gets influenced by extreme observations. Otherwise, seasonality is not a feature of the current Indian stock markets.

1 Market Anomalies: A Discussion

It is possible that if the data is torchured with sufficient intensity, one might find systematic patterns and apparent relations that he is looking for (Sullivan et al., 1998)! So if one is keen on discovering an anomaly in the stock market to earn a quick buck, he just might discover unusual patterns emerging out of the most unusual of occurances. For instance *investopedia* [1] circulated among its subscribers a list of what they called the 'world's wackiest

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[1]http://www.investopedia.com/articles/stocks/08/stock-market-indicators.asp?viewed=1

indicators'. Though much of this had no logic. Nertheless it continue to have an embarrassingly large number of believers. For example, multiplying the change in the butter production in Bangladesh by two will give the percentage by which S&P 500 Index will change the next year. Or "When the majority of a country dislikes the man in the White House, the stock market is supposed to soar."

Leaving these embarrassments apart, there has been scientific economic evidence countering market efficiency. One of the earliest relates to the Capital Asset Pricing Model (CAPM) specification. It was shown that value based measure have higher explanatory power than the beta (Basu, 1977)[2]. This result was later confirmed by Reinganum (1981). They found US stock returns to be positively related with price to earnings ratios. Later, others documented similar relation with Book–to–price ratio and dividend yields[3]. Later Banz (1981) showed that in the US stock markets there is a negative relation between security returns and the market value of the firm. This anomaly is popularly known as the size effect. All these evidences led to the understanding towards a better multi–factor asset pricing models such as the popular Fama–French three–factor model (Fama and French, 1992)[4]. Coming back to anomalies, Shiller (1981) showed that prices wander away from fundamental values since the variation in stock prices are too large to be explained by variation in dividend payments[5]. Coming to long–horizon returns, DeBondt and Thaler (1985) finds that stocks which underperformed over a period of 3 to 5 years average the highest market–adjusted return over the subsequent period. This long-term mis-pricing is seen as an overreaction in the market in which stocks diverge from fundamental value.

Literature also abounds with stock market seasonalites. Documented seasonalities include month-of-the-year, week-of-the-month, day-of-the-week and hour-of-the-day effects. Rozeff and Kinney (1976) first documented that average stock returns in January are higher than any other month. Keim

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[2]CAPM can be specified as:

$$r_j = a_0 + a_1\beta_j + \sum a_j C_{ij} + e_j \tag{1}$$

Where,r_j = Cross sectional returns of security j; β_j = Covariance with the market return; C_{ij} = Security specific characteristics. CAPM predicts that the a_j is zero $\forall j > 1$

[3]The relation with dividen–yield could be due to the differential taxation of capital gains and ordinary income. See Litzenberg and Ramaswamy (1979)

[4]Fama and French suggest that the additional variables proxy risk factors omitted from CAPM

[5]"Measures of stock price volatility over the past century appear to be far too high – five to thirteen times too high – to be attributed to new information about future real dividends" (Shiller, 1981)

(1983) and others[6] also finds the same, that the fifty percent of the annual price premium in the US is concentrated in the month of January, particularly in the first few weeks of the year. This is particularly true for small firm stocks. One explanation attributed to this behavior is the year end related tax selling and the subsequent repurchases in January. By selling stocks that have reduced in prices, particularly smallcap stocks, traders realize a capital loss which can be used to offset capital gains, thus reducing the taxable income. This is popularly known as the tax loss selling hypothesis. Another explanation relates to the portfolio rebalancing by institutional investors. The fund mangers sell small stocks showing losses in the current year and reinvest the funds in selected stocks in early January. The motivation for this is that it will make their annual reports look stronger leading to higher compensation for the manager [7]. Ogden (1990) gives a different explanation for the monthly and January effects. He attribute it, in part, due to the standardization in the payments system (in US). The cash flows is concentrated at the turn of each calendar month. Due to this standardization, investors realize substantial cash receipts at the turn of the month and year. Which, when reinvested leads to a surge in stock returns at the turn of the month. He calls it, the 'Turn of the month liquidity hypothesis', since it depends on the magnitude of aggregate liquid profits realized in the month, which is affected by monetary policy. Since the turn of each month is a typical pay off date, short–term investable funds prefer securities maturing at the end of the calender month to securities maturing either before or after that date [8]. This demand for month end securities causes their prices (yields) to be bid up (down) relative to adjacent maturity securities. In explaining the January Effect he says that his hypothesis is consistent with observed concentration of positive returns in the first few trading days of January. Besides, there is a surge in retail activity at the end of the year (holiday effect) and the consequent liquid profits in December is expected to induce a large surge in stock returns in early January.

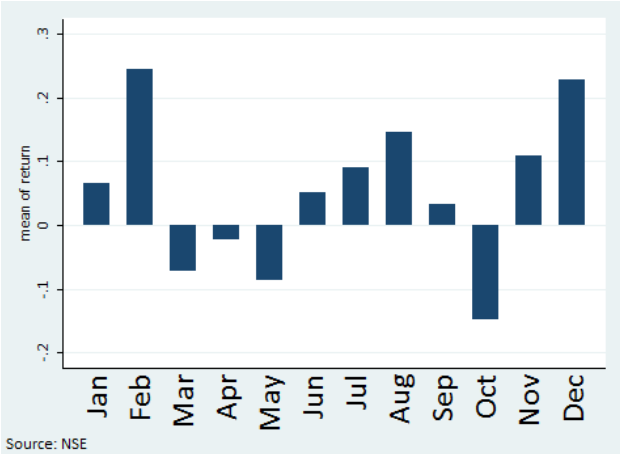
A recent paper by Pandey (2002) which examined the Bombay Stock Exchange's benchmark index 'Sensex' for the period 1991 to 2002 confirm the existence of seasonality and the January effect in the Indian market. He examines seasonality using an augmented dummy variable regression, taking January as the omitted category or benchmark category in the model and

[6] Roll (1983), Reinganum (1983), Ritter (1988)

[7] See Ogden (1990)

[8] If it is in shorter term securities, it may have to be rolled over to provide the necessary liquidity to pay turn of the month obligations. Or if it is in longer term securities it will have to be sold prematurely. Either ways it is suboptimal due to the high interest rate risk and transaction cost invloved.

Figure 1: Mean Monthly Returns



replacing the residuals with an ARIMA model.

But, one feature of financial anomalies is that they tend to disappear soon after evidence of their existence enters the public domain (Bailey, 2005). This is because either they signal profitable investment opportunities which disappear when they become widely known, or because they were never genuine[9]. Here we examine whether the seasonality in monthly returns is a persisting phenomenon in the Indian markets .

2 Seasonality in Nifty: An Exploration

A bar-graph of the mean across the months provides an easy visual explanation of the prevalence of seasonality. Figure 1 is such a bar chart on mean daily returns on Nifty for the period January 1991 to Ocotber 2008 for various months. From the bar-graph we can see that the calender months of February and December has the highest mean daily returns, over and above 0.2%. The month of October register the lowest mean daily return of about -0.14%. The calender months of March, April and May are the only other months reporting negative mean daily returns.

The probability of having negative mean daily returns in each month is computed in table 1. We define the probability of having negative returns simply as the ratio of the frequency of a given month having mean negative returns for the period 1991 to 2008 to the total frequency possible. From this we can see that the calender months of March and April have the highest probability (72% and 67%, respectively), while the December and November

[9] *ibid*

Table 1: Percentage of Times a Month Gave Negative Returns

Month	Jan	Feb	Mar	Apr	May	Jun
%	44%	28%	72%	56%	50%	28%
Month	Jul	Aug	Sep	Oct	Nov	Dec
%	33%	33%	33%	67%	39%	22%

have the lowest (22% and 28%, respectively). But, one should be careful at 'theorizing' at the mere sight of such patterns. For example one can attribute the low returns in October to advance tax-filing or consumers adjusting their cash flows for the upcoming holiday season.

Similarly, March will coincide with the financial year end. One can put forward the tax-loss selling hypothesis, borrowing the idea from the US markets (In the US, financial year coincides with the calender year. The observed low returns during December and high returns during January is attributed to tax-loss selling to reduce the tax-burden in December, which is followed by a buy-back in January). But, unlike in US we don't see buy back the following month leading to an 'April effect'. It might be possible that they are just 'random' occurrence, and might not show any recurring patterns.

It would be more insightful to examine the monthly performance across 'structural breaks'. Sasidharan (2009) has shown that the Nifty series has had four major structural breaks. The break periods were December 1994, July 1999, June 2003 and January 2006. And it was shown that the market has become weak-form efficient only since the third structural break corresponding to June 2003. A 'structural-break-wise' analysis will provide a disaggregated view of the time series, but at the same time provides enough aggregation which an year-to-year analysis cannot provide. Besides, while markets behave differently across different regimes, there might be fair amount of consistency in behaviour within the regimes. Table 2 show the monthly mean daily returns accross structural breaks. The observations from the table 2 can be summarised as follows:

Regime1, Jan'91 to Dec'94: The mean daily returns are highest for February and January (above 0.6%), followed by August (0.45%). April, May and October gave negative returns less than -0.2%

Regime2, Dec'94 to Jul'99: Average daily returns are more than 0.2% during the months of December and February. It is lowest for November. August, October and January also have negative returns

Table 2: Monthly Mean Daily Returns Across Periods

Month	Regime1	Regime2	Regime3	Regime4	Regime5
Jan	0.61	-0.11	0.11	-0.04	-0.25
Feb	0.68	0.24	0.17	0.04	-0.08
Mar	0.02	0.08	-0.42	-0.11	0.04
Apr	-0.23	0.13	-0.24	-0.14	0.34
May	-0.24	0.06	0.05	-0.23	-0.25
Jun	0.11	0.04	0.16	0.21	-0.25
Jul	0.29	-0.02	-0.16	0.26	0.19
Aug	0.50	-0.29	0.18	0.26	0.12
Sep	0.14	0.04	-0.35	0.30	0.10
Oct	-0.25	-0.25	-0.11	0.04	-0.15
Nov	0.12	-0.35	0.38	0.40	0.07
Dec	0.11	0.27	0.12	0.42	0.17

Regime3, Jul‘99 to Jun‘03: Highest positive returns for November and lowest returns for March, followed by September.

Regime4, Jun‘03 to Jan‘06: December and November have the highest daily returns (above 0.4%). May has the lowest returns. April, March and January also have negative returns

Regime5, Jan‘06 to Oct‘08: April registered the highest return and January, May and June has the lowest

Tables 3 and 4 summarizes the top performers and worst performers across these regimes. We can see 7 out of 12 months appearing at different points of time as the worst performers! We neither see consistent January effect nor a tax-loss selling effect. This reminds us of Mark Twain...

> "October. This is one of the peculiarly dangerous months to speculate in stocks in. The others are July, January, September, April, November, May, March, June, December, August and February" [10]

The typical 'monthly effects' that was documented in India was probably the outcome of fitting parametric estimators to a fat-tailed distribution. The effect of extreme values on any mean-based statistic is obvious...it gets pulled towards the extreme observation. Regarding distributional properties, Sasidharan (2009) has shown that the return distribution for Nifty is not Gaussian,

[10] Mark Twain (1894) in *The Tragedy of Pudd'nhead Wilson*, ch 13

Table 3: Month of the Year Effect: The top Performers

Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
February	December	November	December	April
January	February	August	November	July
August	April	June	September	December

Table 4: Month of the Year Effect: The Worst Performers

Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
October	November	March	May	Jan
May	August	September	April	May
April	October	April	March	June

rather it is closer to a Stable Paretain distribution with $\alpha < 1$. This class of distribution is characterised by fat tails, and thus has the property of infinite population variance. Therefore, though estimators based on sample variance is computable, they are not reliable. Under such circumstances it will be preferable to use distribution-free tests.

2.1 Does Seasonality Persists?

If seasonality or month-of-the-year persists, by ranking the months according to the size of their mean daily returns we might see similarity in these ranks across years. But, instead of yearly ranks it would be better to examine it across periods of structural breaks, as it can provide a fair amount of aggregation and, at the same time, provide the essence of persisting patterns. We, therefore, rank months according to their mean daily returns across the five regimes. Then, we test whether these ranks are consistent across the periods by examining rank correlation coefficient between different periods.

Table 5 provides the ranking of months based on the mean daily returns, across the periods of structural breaks. January had ranks ranging from 2 to 11. February ranged from 1 to 8, starting with rank 1 and then slowly departing from the top position to 2, 3, 7 and then 8 in the final regime. March also had sufficient variability ranging from 4 to 12. April had a nearly alternating pattern with highest and lowest ranks ranging from 11 in regime-four to 1 in regime-five. May and June's ranks range from 5 to 12 and 4 to 12 respectively. We can also see that less 'controversial' months such as April and July topping the list in the latest regime. August, which was ranked 11 in second regime, is now ranked 4. November had huge variability moving from 12 in the second regime to rank 1 in the third regime. In the latest regime we can find it at 6. October had a low variability at lower ranks - 9 to 12; and December had the low variability at higher ranks - 1 to 7. In short, we do not see any consistent pattern across these months, and they move around with great variability.

To test for consistency in the rankings we use Spearman's rank correlation coefficient. The computations involved in getting the coefficient between two rankings are as follows: First rank the two series. Obtain D, which is the difference between two. Then the rank order correlation can be computed by the equation:

$$\rho = 1 - \frac{6 \sum D^2}{N(N^2 - 1)} \tag{2}$$

where, N equals the number of pairs and ρ is the rank correlation coefficient. This exercise can be conducted for all pairs of rankings and the results can be presented in a correlation matrix (see table 6). These results can be supplemented using Kendall's coefficient of concordance, which can simultaneously measure the degree of relationship with all the sets of ranks. For this we first compute D^*, is the difference of the sum of the ranks of reach row from this mean. We take sum of ranks and divide it by the number of months to get the average sum of ranks. D^* Next we can use the following formula to compute the Kendall's coefficient of concordance, W:

$$W = \frac{12 \sum D^{*2}}{m^2(N)(N^2 - 1)} \tag{3}$$

Where, m is the number of rankings, which is five in our case; N is the number of cases ranked, which is 12 and W is the Kendall's coefficient of concordance. A perfect agreement is indicated by a W=1 and a lack of agreement by a W=0 (Downie and Heath, 1970).

The results from rank correlation coefficients also confirm our observations from exploratory data analysis that there are no persisting patterns in monthly returns. On examining the results of Spearman's rank correlation coefficients matrix in table 6, we find neither high correlation coefficients nor statistical significance. This result indicate a rejection of the presence of seasonality persisting in the Indian markets. Our computation of Kendall's W

$$W = \frac{12(1500)}{(25)(12)(144 - 1)} = 0.42 \tag{4}$$

also indicates that concordance between the rankings is low.

Sullivan *et al* points out that "In the limited sample sizes typically encountered in economic studies, systematic patterns and apparently significant

Table 5: Ranking of Months Based on Mean Daily Returns Across Periods

Month	Regime1	Regime2	Regime3	Regime4	Regime5
Jan	2	9	6	9	11
Feb	1	2	3	7	8
Mar	9	4	12	10	7
Apr	10	3	10	11	1
May	11	5	7	12	10
Jun	8	6	4	6	12
Jul	4	8	9	5	2
Aug	3	11	2	4	4
Sep	5	7	11	3	5
Oct	12	10	8	8	9
Nov	6	12	1	2	6
Dec	7	1	5	1	3

relations are bound to occur if the data are analyzed with sufficient intensity" (Sullivan et al., 1998). While pointing out to the dangers of data driven inference in analysing calender effects, they also cautions about data snooping bias[11]. They reminds us that none of these calender effects were preceded by a theoretical model predicting their existence. It is not sure whether we have over-indulged in data analysis, but we do suffer from data-snooping bias. At this point, it will be preferable to stop short of theorizing further on the possibilities of any 'month-of-the-year' effect.

3 Conclusion

We see that seasonality is not a recurring phenomenon in the Indian markets. The earlier findings on seasonality could have been the outcome of performing parametric estimates with long time series data, in which case estimators can tend to get influenced by extreme values. As shown elsewhere[12], the distribution of returns need not be normally distributed, but could be a Stable Paretian. This distribution is characterized by fatter tails than predicted by normal distribution, implying that there have been a few

[11] "Like many of the social sciences, economics predominantly studies non-experimental data and thus does not have the advantage of being able to test hypotheses independently of the data that gave rise to them in the first instance. If not accounted for, this practice, referred to as data-snooping, can generate serious biases in statistical inference"(Sullivan et al., 1998)

[12] Sasidharan (2009)

Table 6: Spearman' Rank Correlation Coefficients for Monthly Ranking Across Periodisation

	Regime1	Regime2	Regime3	Regime4	Regime5
Regime1	1				
Regime2	-0.13 (-0.68)	1			
Regime3	0.41 (-0.18)	-0.29 (-0.35)	1		
Regime4	0.41 (-0.17)	-0.23 (-0.47)	0.44 (-0.15)	1	
Regime5	0.08 (0.79)	0.14 (0.64)	-0.21 (0.49)	0.34 (0.27)	1

very large changes that took place during much shorter sub-periods. This would influence parametic estimates, and can mis-lead us to observing January Effect or other such anomalies, when none actually exists. Investment should be followed by the study of sound fundamentals, than based on naive rules to earn easy (or, loose) money.

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