A Study of Calendar Effect on Stocks in the BSE Sensex

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ABSTRACT

The primary objective of this research paper is to find whether calendar effect exists in the BSE Sensex. Calendar effect shows the disparities in stock prices in the stock market subsequent to certain trends based on various time periods of year, various time periods of the month, and various days of the week. This type of tendencies/regular patterns happen at a definite time period in any calendar year.
We utilized BSE Sensex data for a period of twelve years, starting from 2005 to 2016 to explore possible patterns of buy-sell months that would result in a minimum level of profitability.

Keywords: Data Analytics, Data Mining, Calendar Effect, BSE Sensex, January Effect, Weekend Effect.

INTRODUCTION:

Data analytics is mainly concerned with analyzing huge volumes of data with the purpose identifying patterns from the data. Data mining as a discipline is evolving and new tools are being developed to find meaningful insights from data. Data mining has variety of applications and is used effectively in several fields. Data mining and other data analytics tools can be effectively applied in the stock market for the purpose of prediction of future stock prices. By its very nature stock market is volatile and unpredictable. Even well experienced investors and stock brokers are not able to predict the stock market accurately. There is an influence of internal and external factors on price of stocks. Fundamental and technical analysis is conducted by analysts to predict the stock prices. Fundamental analysis makes use of factual and data available in the public domain to evaluate a stock's value. Technical analysis of stocks is the study of past market data, including volume and price. Inspite of using these methods, anomalies like calendar effect are observed in the stock market.

Irregularities in returns from the stock market that are related to the calendar are collectively identified as calendar effects. These effects can be day-of-the-week, the month-of-the-year, or holiday effects. Some of the well-known examples of calendar effects are January effect and Monday effect. A number of past studies have examined the occurrence of calendar effects in various stock markets. Due to calendar effects, the returns tend to show higher or lower than average returns in specific calendar periods. Significant calendar effects that have been investigated previously are: (i) January Effect, past researchers have found that daily returns tend to be higher in January as compared to other months in most of the years and (ii) Weekend Effect, because of which Monday returns are likely to be lower than on any other days of the week, and quite often Friday returns are likely to be higher.

Other prominent calendar effects that were investigated by the past researchers are:
 a) Holiday effects, for which the trends in returns after non trading holidays are studied, and
 b) Day of the month effects, in case of which higher returns are found in definite periods of the month

REVIEW OF LITERATURE:

Past investigators have investigated the presence of seasonality in stock markets in terms of price movements, associated with definite periods in a calendar. The two most well investigated calendar effects are: (a) Month of the Year Effect, and (b) Day of the Week Effect. Also, several past studies examine other types of calendar effects. These studies have investigated calendar effects such as returns in the first trading days of each month, daily returns after holidays, etc.

Day of the Week Effect:

Osborne (1962) pioneered to study this effect, it was further analyzed by Cross (1973), Gibbons and Hess (1981), Jaffe and Westerfield (1985), Rogalski (1984) and Keim and Stambaugh (1983). These researchers found that expected returns in stock markets are not the same for all weekdays. French (1980) found that returns were negative on Mondays however they were positive on other days of the week. Levi (1978) found that weekend returns were influenced by settlement effect. Jaffe and Westerfield found that Weekend Effect existed in stock markets of Canada, Australia Japan, and Hong Kong. Lakonishok and Maberly (1990) stated that stock trading on Monday was the result of low cost opportunity as compared to trading in other week days. Stickel (1995), Groth et al (1979), Ho and Harris (1998), Womack (1996), among investor selling activity as the prime cause underlying the Monday Effect. Additional proof of stock return patterns for a variety of countries related to the day of the week was found by Condoyanni et al. (1987), Bruno Solnik and Laurence Bousquet (1990), and Aggarwal and Rivoli (1989).

Amanulla. S and Thiripalraju (2001) who investigated the Indian stock markets found the existence of Week End Effect. They stated that due to this effect returns were found to be consistently negative on Tuesdays and consistently positive on Wednesdays. Research on Day of the Week Effect was conducted by Hareesh Kumar. V and Malabika Deo (2007) with respect to the Indian Stock Market. They studied the Stock Market in India by using S&P CNX 500 Index in order to find its efficiency. They found that the Indian Stock Market was inefficient due to the presence of abnormality such as Day of the Week Effect. This abnormality had an effect on stock returns as well as volatility. A study on Indian Stock Market with respect to the Week End Effect was done by Nageswari and Babu (2011). These researchers found positive mean returns for every trading day of the week. They observed that the returns lowest on Monday and were highest on Friday. They arrived at a conclusion that the Indian Stock Market did not display Day of the Week Effect during period of the study.

Month of the Year Effect:

Ariel (1987) found that, on an average, rates of return were significantly lower during the second half of the month as compared to the first half. This research found that month of the year effect occurred in USA as well as few other developed countries. The research revealed that the return was higher in January month and in December was generally lower in comparison to returns in other months. Similar results were found by Jeffrey Jaffe and Randolph Westerfield (1988) in their investigation of stock markets of Australia, UK, Japan, and Canada. This research found that returns over the second half of the month were lower than the returns over the first half for Australia, UK and Canada.

Wachtel (1942) was the first researcher to investigate the January Effect. Haugen and Lakonishok (1988) studied the January Effect in detail and has authored a book on this well-known calendar effect. Kok Kim Lian (2002) studied the Year of Month Effect and Half Month Effect in the Asia-Pacific stock markets. They found Year of Month Effect to be prevalent in all stock exchanges but found that Half Month Effect was relatively weak and unstable. Selvarani. M and Leena Jenefa (2009) found the existence of January and April Effect in the NSE.

Chotigcat. T and Pandey I M. (2005) investigated the impact of Monthly Effect for the Indian and Malaysian stock markets with respect to stock returns. The study confirmed the presence of seasonality in stock returns in both capital markets. Ushad Subadar Agathee (2008) did a study on Stock Exchange of Mauritius (SEM). They found that average returns of SEM were lowest in March and highest June.

A Gap in the Past Literature is that there is no systematic study on the stock markets of the effect of buying in a particular month and selling in a different month. Specially there is no study which is concentrating specifically on Calendar Effect in BSE Sensex with respect to Month of the Year Effect. There is a need to investigate whether anomalies exist in the Indian stock market. If anomalies like Calendar Effect exists, it will lead to unfair advantage to some traders in the stock market who will in turn use it to their advantage.

For the purpose of this study the researchers worked with a threshold of 5% monthly returns between the buy and sell months identified as a significant return. We utilized published past data from NSE and applied analytics techniques to look for possible patterns in buy sell months.

RESEARCH METHODOLOGY:

Research Objective:
- To find whether Calendar Effect exists in the BSE Sensex.
- To investigate whether buy-sell month has an impact on Calendar Effect in BSE Sensex.

Analysis of Data:

The researchers utilized data available for the 30 shares in the BSE Index for the last 12 years. The independent

variables utilized in the models were Individual firms, Industry Classification code as per NIC, Buy-Sell Month, Closing Stock Price, Earnings per Share. Related to the individual shares in the buy month were the Number of Shares traded, Number of Trades, Turnover, Percentage Delivery, spread between high-low in the buy month and spread between open-close prices of the share. The dependent variable was the potential Profit or Loss in a transaction over buy-sell months.

The target variable, the profit-loss incurred while buying in a specific month and selling in another specific month was calculated using the average price of the share in the buy and sell month. The Buy – Sell month combinations were taken over a 12-month period resulting in 66 records for each share for every year of data. (Hence for each share a buy month of January, would have 11 combinations with sell months of February, March, April… December resulting in (11 x 12)/2 combinations.) For the initial trials, the researchers took only 10 shares and 2 years of data ensuring each of these shares was present in the BSE Index for the 10 years 2006-2015. The researchers attempt was to eventually utilize the complete 10 years' data to study any effect on the model created using 4 years of data.

Stock data for the years 2005, 2006, 2015 and 2016 was used for these initial trials. With the combination of buy-sell months this resulted in a total of 2640 records. The outliers in the data were removed (where the average monthly profit-loss figures were above 25%). These unusually high returns were most likely due to some exceptional event which will not be a part of general pattern. Including outliers would distort the pattern extracted by an analytics model. This resulted in a deletion of 128 records.

The researchers used the continuous variables without categorization in a KNN model and with categorization for a Naïve Bayes model. All the continuous independent variables were converted into 5 categories.

A sample of the data and categorization is shared in Appendix Table 1.

FINDINGS AND DISCUSSION:

We used Naïve Bayes in our initial model which consistently produced error rates of over 23 %. Derived variables and additional data did not help reduce the errors substantially. The results are shared in Appendix Tables 2 and 3. Logistic Regression produced slightly better results with error rates of 22% (Appendix Table 5). Decision Tree models including Random Forests performed equally poorly with error rates above 29%.

Subsequent trials with a KNN model produced much better results and error rates of below 20 %. (Appendix Tables 6 and 7). The best model was with K= 1 an error rate of 18.5 %.

For further confirmation of the above, the researchers looked for associations between the buy-sell month and Profit Categories (avg. monthly returns above 5% / below this) using a Market Basket Analysis. Across the 66 combinations there was only 1 buy-sell month (Oct-Nov) which showed some degree of dependence.

The Naïve Bayes model produced consistently higher error rates than the KNN model and it appears the loss of information in the categorization of the variables is detrimental to the discovery of patterns in the data for prediction of profitability.

A KNN model appears to detect a pattern in profitability with the variables turnover in the buy month, number of Shares traded, number of Trades, Turnover, Percentage Delivery, spread between high-low and spread between open-close prices of the share in the month.

CONCLUSION:

Traditionally studies of calendar effects on stocks have focused on daily effects with day of the week, post-holiday effects dominating the studies. This study looked at a buy month to sell month effect and created a model that could be used to guide an investor's decisions in a market.

Independent variables with a KNN model appears to be better in extracting a pattern in the profitability (using the variables shortlisted). Naïve Bayes and Logistic Regression produced lower accuracy models. The accuracy of the models in detecting profitable buy-sell months is low suggesting that Calendar Effect may not be a reality.

The Calendar Effect appears to be a result of the changes in the trading patterns and is not specific to buying in a specific month and selling in another specific month. The profitability prediction is better with the known variables that drive buying sentiment and selling sentiments in the markets.

FURTHER WORK:

The current model is based on a simple and fast technique for classification. It is highly dependent on the 30 shares index data and may not be effective when generalized to other stocks. Further, the researchers have utilized only 2 categories of profitability and an extension of this into multiple categories would create a more

useful prediction framework.

Work is ongoing for more testing using non index stocks and creating a model where the specific firm relevance is removed.

As this work leads the researchers to conclude that the calendar effect of buy-sell month is not dependent on the specific months but on the data in the other relevant variables, the next phase of this project is to explore the difference in the values of these variables in the buy-sell months. The researchers propose to add 'sentiment' as an additional variable for the buy-sell months.

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APPENDIX:

Table 1: BSE data for the 10 shares

Firm Year	BS Index	Industry	PL	PL_cat_ monthly	No. of Shares	Cat_ BUY No. of Shares	No. of Trades	Cat_ BUY _No. of Trades	Cat_ BUY_Total Turnover (Rs.)
1	1	1	0.013973	0	3107028	0	57753	1	0
1	2	1	0.021239	0	3107028	0	57753	1	0
1	3	1	-0.06083	0	3107028	0	57753	1	0
1	4	1	0.030275	0	3107028	0	57753	1	0
1	5	1	0.07741	0	3107028	0	57753	1	0
1	6	1	0.143642	0	3107028	0	57753	1	0
1	7	1	0.204844	0	3107028	0	57753	1	0

Table 1: BSE data for the 10 shares (Continued)

Cat_BUY_ Deliverable Quantity	Cat_BUY_% Deli. Qty to Traded Qty	Cat_BUY _Spread High-Low	Cat_BUY_ Spread Close-Open	Cat_Close price	Cat_EPS	Cat_P/E
0	3	0	4	2	1	1
0	3	0	4	2	1	1
0	3	0	4	2	1	1
0	3	0	4	2	1	1
0	3	0	4	2	1	1
0	3	0	4	2	1	1

Table 2: Naïve Bayes Training Data Scoring - Summary Report

Cut-off probability value for success (UPDATABLE) 0.5			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	124	267	
0	103	1090	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	391	267	68.28645
0	1193	103	8.633697
Overall	1584	370	23.35859
Performance			
Success Class	**1**		
Precision	0.546256		
Recall (Sensitivity)	0.317136		
Specificity	0.913663		
F1-Score	0.401294		

Table 3: Naïve Bayes Validation Data Scoring - Summary Report

Cut-off probability value for success (UPDATABLE) 0.5			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	78	176	
0	73	729	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	254	176	69.29134
0	802	73	9.102244
Overall	1056	249	23.57955
Performance			
Success Class		1	
Precision		0.516556	
Recall (Sensitivity)		0.307087	
Specificity		0.908978	
F1-Score		0.385185	

Table 4: Logistic Regression Training Data Scoring - Summary Report

Cut-off probability value for success (UPDATABLE) 0.5			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	68	313	
0	41	1085	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	381	313	82.15223
0	1126	41	3.641208
Overall	1507	354	23.49038
Performance			
Success Class		1	
Precision		0.623853	
Recall (Sensitivity)		0.178478	
Specificity		0.963588	
F1-Score		0.277551	

Table 5: Logistic Regression Data Scoring - Summary Report

Cut-off probability value for success (UPDATABLE) 0.5			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	35	192	
0	32	746	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	227	192	84.5815
0	778	32	4.113111
Overall	1005	224	22.28856

Performance		
Success Class	1	
Precision	0.522388	
Recall (Sensitivity)	0.154185	
Specificity	0.958869	
F1-Score	0.238095	

Table 6: KNN Report (for k = 1) Training Data Scoring - Summary

Cut-off probability value for success (UPDATABLE)			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	311	70	
0	86	1040	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	381	70	18.3727
0	1126	86	7.637655
Overall	1507	156	10.35169
Performance			
Success Class	1		
Precision	0.783375		
Recall (Sensitivity)	0.816273		
Specificity	0.923623		
F1-Score	0.799486		

Table 7: KNN Report (for k = 1) Validation Data Scoring - Summary

Cut-off probability value for success (UPDATABLE) 0.5			
Confusion Matrix			
	Predicted Class		
Actual Class	**1**	**0**	
1	147	80	
0	106	672	
Error Report			
Class	**# Cases**	**# Errors**	**% Error**
1	227	80	35.24229
0	778	106	13.62468
Overall	1005	186	18.50746
Performance			
Success Class	1		
Precision	0.581028		
Recall (Sensitivity)	0.647577		
Specificity	0.863753		
F1-Score	0.6125		