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THE MONTH-OF-THE-YEAR EFFECT IN THE INDIAN STOCK MARKET: A CASE STUDY ON BSE SENSEX

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Abstract *Efficient Market Hypothesis proposes that it is not possible to outperform the market through market timing. However, research studies over the years have reported several anomalies in stock market returns. Anomalies that are linked to a particular time are called calendar effects.The month-of-the-year effect or particularly the January effect is one of such anomalies. The present study in this context has sought to address the issue of the month-of-the-year effect in Indian Stock Market represented by BSE SENSEX during the period ranging from January 2, 2004 to December 28, 2012. The GARCH(1,1)-M model has been used to model the conditional volatility. The results indicate the presence of September and November effects in the SENSEX returns during the study period. Moreover, in the volatility equation the coefficients of March, June, August, October, November and December dummy variables are negative and significant. Hence, it is confirmed that the month- of- the year effect is also present in the variance (volatility or risk) equation.*

Keyword: *Month-of-The-Year Effect, Return, Volatility, GARCH-M*

INTRODUCTION

According to Fama (1965), the proponent of Efficient Market Hypothesis, the expected return on a financial asset should be uniformly distributed across different units of time. However, researchers have documented several calendar anomalies in the stock returns. One of such anomalies is the month-of-the-year effect. The month-of-the-year effect would exist if returns on a particular month are higher than other months. Rozeff and Kinney (1976) observed that average stock returns in January are significantly higher than any other. Keim (1983) investigated the seasonal and size effects in stock returns and found that small firm returns were significantly higher than large firm returns during the month of January. It is said that investors, in order to reduce their taxes, towards the end of the year, sell shares whose values have declined. By selling stocks that have reduced in prices, particularly small cap stocks, traders realize a capital loss which can be used to off set capital gains.This lowers stock returns by putting a downward pressure on thestock prices. As soon as the tax year ends, investors start buying shares and stock prices bounce back. This causes higher returns in the beginning of the year (in the month of January).This argument is termed as 'tax-loss selling' hypothesis (Branch,1977). Reinganum (1983) found that companies with largest price declines exhibited highest returns during first days in January. Hence, at least a part of the January effect could be described by tax-loss selling hypothesis. However, Roll (1983) mentioned that though sales would be higher in December to avoid tax paying, other investors would buy the stocks sold in anticipation of an eventual increase in January and this would eliminate the January effect. He further argued that there was evidence of January effect in other countries where there was no tax imposed on capital gains and also in countries where tax year does not begin in January. Brown *et al*. (1983) reported a January effect in Australia though the tax year ends in June in Australia. Another explanation regarding this is related 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 better leading to higher compensation for the manager (Keim, 1983). Recently, Easterday and Stephan (2006), re-examined the joint small firm/January effect proposed by Keim (1983), over a 62-year period of study but broke it into three distinct sub-periods: 1963-1979 (the same years as taken by Keim, 1983), 1943-1962 and 1980-2004. They found that the returns in January for small firms were significantly higher to other months in 1963-1979(Keim period), but for the pre and post Keim period the returns were remarkably lower.

In India the tax year ends in March, thus an April effect may be observed according to the 'tax-loss selling' hypothesis. The present study has sought to address the issue of the month-of-the-year effect in Indian Stock Market represented by BSE SENSEX.

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LITERATURE REVIEW

Pandey (2002) studied the presence of the seasonal or monthly effect in stock returns. This study investigated the existence of seasonality in the post-reform period. The study used the monthly return data of the SENSEX for the period from April 1991 to March 2002 for analysis. After examining the stationarity of the return series, an augmented autoregressive moving average model is specified to find the monthly effect in stock returns in India. The results confirmed the existence of seasonality in stock returns in India and the January effect.

Lazar *et al.* (2005) using data from SENSEX investigated the monthly effect in the stock returns in India. Their results confirmed the existence of seasonality in stock returns in India consistent with the 'tax-loss selling' hypothesis.

Sah (2008) found evidence for a Friday effect and monthly anomalies for July, September, December, and January in S&P CNX Nifty.

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) found 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.

Dash (2011) conducted his study to explore the interplay between the month-of-the-year effect and market crash effects on monthly returns in SENSEX. 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 provided evidence for a month-of-the-year effect in Indian stock markets, particularly positive November, August, and December effects and a negative March effect.

The study conducted by Nageswari and Selvam (2011) found that the monthly effect pattern did not appear to exist in the Indian Stock Market during the study period of ten years from 1st April 2000 to 31st March 2010.

Ray (2012) using monthly closing share price data of SENSEX from January, 1991 to December, 2010 for this purpose. The results of the dummy variable regression provided evidence for a month-of-the-year effect in Indian stock markets confirming the seasonal effect in stock returns in India and also support the 'tax-loss selling' hypothesis and 'January effect'.

In his study, Debasish(2012) presented an analysis of the stock price behaviour on the seasonality effect. The period Indian stock market. The seasonality effect is examined by a detailed analysis of month of the year effect, the period of study spans over five years i.e. from 2006 to 2010. With the help of multiple regressions, the study found evidence of month of year effect for the price series with regard to the selected companies. On the whole, the price series in the Indian stock market showed signs of return seasonality with respect to month of the year effect.

Verma and Kumar (2012) examined month-of-the-year effect by using Kruskal-Wallis test for equality of means and the ordinary least squares (OLS) regression with the dummy variables. The results of Kruskal-Wallis test indicated no significant difference in the average returns across the months over the period of study. The regression results indicate no significant difference between the returns of January vis-à-vis each of the remaining months of the year over the period of study.

DATA AND METHODOLOGY

Data

The data used in this study are daily BSE SENSEX returns for the period from January 2, 2004 to December 28, 2012 (a total of 2224 observations). The data have been obtained and downloaded from the website www.finance-yahoo.com. Daily Market Returns (R_t) have been computed as follows:

$R_t = \ln(I_t) - \ln(I_{t-1})$

Where, ln denotes natural logarithm

I_t is the closing index value at day 't'

I_{t-1} is the closing index value at day before 't'

Methodology

In order to effectively determine the presence of the month-of-the-year effect in daily returns and volatility and taking into account the time varying property of volatilities, the

GARCH-M model has been used:

$$R_t = \alpha_0 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \alpha_5 D_5 + \dots\dots\dots\dots$$
$$+\alpha_{11} D_{11} + \alpha_{12} D_{12} + \sum_{i=1}^{n} \alpha_i R_{t-i} + \lambda \sigma_t + \varepsilon_{i,t}$$

(1)(mean equation)

$$\sigma_t^{\,2} = V_C + V_2 D_2 + V_3 D_3 + \dots\dots + V_{11} D_{11} + V_{12} D_{12} + V_{1a} \varepsilon_{t-1}^{\,2} + V_{1b} \sigma_{t-1}^{\,2}$$

(2) (Variance equation)

where Rt represents returns on a selected index, D_2, D_3, etc are the dummy variables for February, March etc.For example, D_2 takes a value of 1 for all February observations and zero otherwise and so on. In order to avoid the dummy variable trap any dummy variable representing the month of January has not been included, α_0 represents the mean return of January. λ is a measure of the risk premium. If λ is positive, then risk averse agents must be compensated to accept higher risk. To solve the possible problem of autocorrelation lagged values of returns have also been incorporated. This model incorporates the month of the year effect for both the return and volatility equations by using the Modified-GARCH (1,1) specification.

For non-negativity, $V_{1a} \geq 0, V_{1b} \geq 0$ and $V_{1a} + V_{1b} < 1$.

If coefficients of dummy variable are significant then there is month-of-the-year effect in returns or volatility or both.

In order to determine the month of the year effect, one must test whether the variables for all months are jointly zero. However, due to the high degree of non-linearity of the model and the high correlation among the month of the year dummy variables, following Kiymaz and Berument (2003), the month of the year effect if any months daily return (or volatility) is different from any other months (here January), rather than every single month's return (or volatility) being equal to that of the others have been tested.

EMPIRICAL RESULTS

Descriptive Statistics

The descriptive statistics of daily market returns (month wise) have been presented in the Table 1.

It could be seen that the minimum and maximum daily returns during the study period are -0.118092 and 0.15990 respectively (both surprisingly in the month of May). So a wide range of fluctuation in daily returns could be witnessed. The lowest mean daily return is -0.00056 which also been observed in the month of May. Highly significant large JB statistic confirms that the return series is not normally distributed.

Unit Root Test

The time series data used in the empirical study must be stationary. If the data is non-stationary then regression results using such data would be spurious, because the usual 't' test would not be applicable to test the significance of coefficients.

To test the stationarity the unit root test is applied on the time series return data. In this regard the Phillips-Perron Unit Root Test is used. In Phillips-Perron Test non-parametric statistical methods are used to take care of the serial correlation in the error term (μ_t) of the following equation:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \mu_t \quad (3)$$

where Y_t is the time series data under consideration.

The test is based on the null hypothesis H_0 : Y_t is not I(0). If the absolute PP statistics are greater than the critical value then Y_t is stationary.

The PP test result is reported in the Table 2. The computed value of PP is -44.04 which is far greater than the critical value of -3.4333 at 1% significant level, if absolute value is concerned. Therefore, it appears that the variable used in this study is stationary at its level.

Table 1: Descriptive Statistics of Daily SENSEX Returns (Month wise)

Month	Mean	StDev	Median	Min	Max	Skewness	Kurtosis	J-B	Obs.
Jan	-0.00106	0.018592	-0.00079	-0.07696	0.06409	-0.35055	2.9253	56.652*	180
Feb	-0.00043	0.014741	0.000152	-0.04893	0.04710	-0.38546	0.9751	10.8857*	175
Mar	0.000797	0.017256	0.002321	-0.06224	0.05893	-0.42202	2.1336	36.6892*	189
Apr	0.001814	0.014114	0.001319	-0.04833	0.04413	-0.25935	1.0799	9.1454*	170
May	**-0.00056**	0.022818	0.000753	**-0.11809**	**0.1599**	1.123963	16.629	1568.47*	191
Jun	0.000155	0.016577	0.001428	-0.0484	0.0666	0.093783	1.6935	15.971*	195
Jul	0.001595	0.016595	0.001092	-0.06008	0.05772	-0.1485	2.2288	26.111*	196
Aug	0.000194	0.012938	0.000358	-0.04379	0.03608	-0.33219	1.2524	10.0807*	193
Sep	0.002664	0.013202	0.003316	-0.04213	0.05313	-0.32408	2.6782	46.938*	186
Oct	-0.00104	0.021817	-0.00129	-0.11604	0.07900	-0.63815	6.1107	223.87*	180
Nov	0.000806	0.016499	0.001622	-0.06839	0.05580	-0.12456	3.0693	53.223*	182
Dec	0.0015	0.013503	0.001198	-0.03917	0.05367	0.309261	2.2288	24.849*	187

* significant at1% level

Table 2: Unit Root Test Results

Variable	Computed PP
Daily SENSEX Return Series	-44.04*

* Significant at 1% levtel

Auto- Correlation Test

To judge the auto-correlation of the time series returns data under consideration Box-Pierce Q statistic in the following form has been used.

$$Q = n \sum_{k=1}^{m} \rho \wedge 2k \quad \sim \chi 2$$

where n=sample size and m= lag length. Since the present study uses daily data a lag length up to 22 has been considered. The reason behind this is that there could be at most 22 trading days in a 30 days month.

If the computed Q statistic is significant then it indicates the presence of auto-correlation.

The Q statistics of return time series data for lag 1 and lag 22 have been reported in Table 3.

Table 3:. Box-Pierce Q Statistics of Return Time Series Data

Lag	Q statistic	Probability
1	9.9214	0.000
22	56.389	0.000

From Table 3, it is clear that Q statistics are highly significant. Hence, the return series is serially correlated.

Results of GARCH-M Model

The estimated results of equation 1 and 2 have been presented in Table 4.

Table 4: Estimated Results of GARCH-M Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Return Equation (Equation…1)				
λ	0.036507	0.064276	0.567969	0.5701
C	-0.000667	0.001380	-0.483327	0.6289
D2	0.000682	0.001535	0.444531	0.6567
D3	0.001546	0.001472	1.049714	0.2938
D4	0.000755	0.001501	0.503122	0.6149
D5	0.000384	0.001472	0.260749	0.7943
D6	0.001936	0.001399	1.383812	0.1664
D7	0.001173	0.001392	0.842572	0.3995
D8	0.000921	0.001309	0.703604	0.4817
D9	0.004195	0.001429	2.935552*	0.0033
D10	0.000860	0.001411	0.609927	0.5419
D11	0.002660	0.001365	1.948830**	0.0513
D12	0.001775	0.001370	1.295361	0.1952
AR(1)	0.058952	0.023450	2.513978*	0.0119
Variance Equation (Equation …2)				
V_c	1.11E-05	3.25E-06	3.407956*	0.0007
V_{1a}	0.118444	0.011468	10.32855*	0.0000
V_{1b}	0.865301	0.011568	74.80061*	0.0000
D2	-5.96E-06	4.31E-06	-1.382558	0.1668
D3	-7.65E-06	3.89E-06	-1.96576**	0.0493
D4	-4.05E-06	4.27E-06	-0.949657	0.3423
D5	-3.72E-06	4.17E-06	-0.891867	0.3725
D6	-8.76E-06	3.57E-06	-2.456999*	0.0140
D7	-6.72E-06	3.47E-06	-1.936532	0.0528
D8	-1.03E-05	3.45E-06	-2.992734*	0.0028
D9	-1.74E-06	3.52E-06	-0.494278	0.6211
D10	-9.29E-06	3.91E-06	-2.372714*	0.0177
D11	-7.92E-06	3.42E-06	-2.31540**	0.0206
D12	-7.51E-06	3.70E-06	-2.02831**	0.0425

* significant at 1% level
** significant at 5% level

From Table 4 it is clear that the coefficients of D_9 and D_{11} Dummy Variables in the equation 1 are significant. So it could be said that there is September and November effects in the SENSEX returns during the study period.Chakrabarti and Sen (2007) found that at market level the November effect was present. It is noteworthy that λ is not significant in equation 1. This result would indicate that positive risk-return relationship does not hold during this period. In other words investors do not want to bear extra risk even for a greater compensation.

The estimated volatility coefficients for the constant terms, as well as the Error term and GARCH term, are positive and statistically significant. This finding satisfies the non-negativity of the conditional variances. $V_{1a} + V_{1b} = 0.98$ which is approaching 1.00. Hence, shocks to volatility persist over time.

In the volatility equation the coefficients of March, June, August, October, November and December dummy variables are negative and significant. Hence, it is confirmed that the month- of- the year effect is present in the variance (volatility or risk) equation.

To see whether any ARCH effect is still present or not Q statistic on the squared residuals of the GARCH-M model has been calculated and the result has been reported in Table 5.

Table 5:. Box-Pierce Q Statistics of Squared Residuals

Lag	AC	PAC	Q-Stat	Prob
1	0.002	0.002	0.0133	
2	-0.018	-0.018	0.7545	0.385
3	0.022	0.022	1.8166	0.403
4	0.030	0.030	3.8606	0.277
5	-0.018	-0.017	4.5658	0.335
6	-0.004	-0.003	4.6017	0.466
7	-0.018	-0.020	5.3289	0.502
8	-0.025	-0.026	6.7599	0.454
9	-0.014	-0.013	7.1806	0.517
10	0.033	0.033	9.6335	0.381
11	-0.025	-0.023	11.017	0.356
12	-0.008	-0.005	11.162	0.430
13	0.009	0.007	11.352	0.499
14	0.002	-0.001	11.358	0.581
15	-0.007	-0.005	11.456	0.650
16	0.010	0.009	11.693	0.702
17	-0.014	-0.015	12.160	0.733
18	-0.002	-0.001	12.168	0.790
19	-0.009	-0.010	12.367	0.828
20	-0.001	-0.003	12.370	0.869
21	0.017	0.020	13.041	0.876
22	0.025	0.025	14.480	0.848

Since none of the Q statistic at any lag is significant so no ARCH effect is left.

A test for the presence of ARCH in the residuals has also been calculated by regressing the squared residuals on a constant and p lags, here p has been taken as 5 (Engle,1982).

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{s=1}^{p} \beta_s \varepsilon_{t-s}^2 \right) + v_t \tag{4}$$

The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Observed*R-squared statistic is Engle's LM test statistic, computed as the number of observations times the from the test regression. The exact finite sample distribution of the F-statistic under H_0 is not known, but the LM test statistic is asymptotically distributed as a $\chi^2(p)$. If F-statistic and the LM statistic are found significant then there is ARCH effect. The results have been presented in Table 6.

Table 6: ARCH-LM test Results

Heteroskedasticity Test: ARCH			
F-statistic	**0.904724**	**Prob. F(5,2212)**	**0.4769**
Obs*R-squared(Engle's LM test Statistic)	4.526633	Prob. Chi-Square(5)	0.4763

Test Equation: 3				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 02/17/13 Time: 12:28				
Sample (adjusted): 7 2224				
Included observations: 2218 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.979793	0.062072	15.78488	0.0000
WGT_RESID^2(-1)	0.003607	0.021258	0.169687	0.8653
WGT_RESID^2(-2)	-0.017844	0.021238	-0.840207	0.4009
WGT_RESID^2(-3)	0.021994	0.021235	1.035745	0.3004
WGT_RESID^2(-4)	0.029749	0.021238	1.400777	0.1614
WGT_RESID^2(-5)	-0.017194	0.021252	-0.809074	0.4186
R-squared	0.002041	Mean dependent var		1.000148
Adjusted R-squared	-0.000215	S.D. dependent var		1.895595
S.E. of regression	1.895799	Akaike info criterion		4.119860
Sum squared resid	7950.049	Schwarz criterion		4.135291
Log likelihood	-4562.924	Hannan-Quinn criter.		4.125496
F-statistic	0.904724	Durbin-Watson stat		2.000176
Prob(F-statistic)	0.476937			

From Table 6, it appears that both the F-statistic and the LM-statistic are insignificant, confirming that no ARCH effect is left.

CONCLUSION

The present study has sought to investigate whether month-of-the-year effect is present in the BSE SENSEX return series during the selected study period from January 2, 2004 to December 28, 2012 (a total of 2224 observations). It has been found that there is a September and November effect in the SENSEX returns during the study period. Interestingly there is no April effect in the market thus the 'tax-loss selling' hypothesis is not applicable during the study period. In the volatility equation the coefficients of March, June, August, October, November and December dummy variables are negative and significant. Since $V_{1a} + V_{1b} = 0.98$, which is approaching 1.00. Hence, shocks to volatility persist over time.

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