Seasonality in the Returns: A Study of BSE Sensex

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Abstract:

The presence of seasonal/monthly effect in stock returns was investigated using monthly return data of BSE Sensex for the period April 2004 to March 2012. After examining the stationarity of the return series, an Autoregressive Moving Average (ARMA) model is specified to find the monthly effect in stock returns. The results do not confirm the existence of seasonality in stock returns and the January effect. The findings are also inconsistent with 'Tax-loss selling' hypothesis. The results of the study imply that the stock market is efficient. The study suggests analysing the 'Day of the Week' effect to enable the investors to devise better strategies to improve their returns.

Keywords: Stationarity, Seasonality, ARMA, Tax-Selling Hypothesis, Market Efficiency

1. Introduction

The Indian Capital Market has witnessed plethora of developments like the introduction of online trading, introduction of derivatives, rolling settlement, dematerialization of shares etc. With the advent of globalization, more attention has been given to the Indian Capital Market. The increase in the BSE Sensex from 2518 points in 1992 to 18000 points in 2012 shows the growth over the years. Emerging markets like India are subject to examination of seasonality in the stock returns. Seasonality refers to the regular fluctuation in a time series which occurs periodically over a span of less than a year. The main cause for seasonality of returns is due to the changes in the economic climate of a country. Stock returns exhibit systematic patterns oat certain times of the day, week or month. Numerous studies have supported the presence of seasonality either in terms of a day, week or month. The existence of seasonality of stock returns have violated Efficient Market Hypothesis.(EMH). A Capital Market is said to be efficient if it fully and correctly reflects all relevant information with respect to an information set implying that it is impossible to earn abnormal returns by trading on that particular information. In other words, the market price of an asset should be equal to the fair value of the asset. However, several market anomalies contradicting Efficient Market Hypothesis have been reported. Such anomalies are primarily due to behavioural causes. The existence of seasonality has violated the weak form of efficiency since the price pattern is no longer random and can be predicted based on the past pattern. If this is the case, it would help the traders to devise trading strategies accordingly. For instance, if month of the year effect is evidenced, the investors may sell the securities in the month of March and buy such securities in the month of April. One of the explanations given for seasonality of returns is 'tax-selling' hypothesis. The definition of financial year is different in India visa vis the U.S. The financial year in India is April-March and in the U.S, it is January-December. For instance, the firms in the U.S may sell shares whose value is less in the month of December to book losses and start acquiring shares in the month of January thus resulting in increase in share prices. This leads to higher returns in the month of January and is termed as 'January Effect'. It would be interesting to analyse whether the seasonality witnessed in U.S is the same or different in India.

2. Literature Review

The following are the review of earlier studies relating to seasonality of returns:

Ansuhman *et al.*, (2000) examined the day of the week effects on the Bombay Stock Exchange during the period 1991-1996 and found evidence of excess positive returns on Fridays and excess returns on Tuesdays.

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Harishankar *et al*., (2004) analysed the day of the week effect in stock return by taking the daily closing price index of the BSE Sensex for the period 1992-2000. The authors have used ANOVA to study the mean return of the trading days. The results of the study indicate that the mean returns on all the trading days of the week are equal and the mean returns are equal across Friday and Monday.

I M Pandey (2002) examined the seasonality in SENSEX monthly returns during the period 1991-2002. The augmented auto regressive moving average model was used to find the monthly effect and seasonality was found to be existing and the lowest returns occurred in the month of October.

Islam *et al*., (2002) examined the Bangladesh stock market to test the normality of stock returns and found the stock returns were higher in January, June, September and October when compared to other months. The study utilized monthly time series data on the DSE stock price index from September 1986 to November 1999 and the returns were found to deviate from the normal distribution for only four out of the twelve months and thus proving the existence of a monthly effect.

Gao *et al*., (2005) examined calendar effects in Chinese stock market particularly monthly and daily effects. Using individual stock returns, the authors observed the change of the calendar effect over time. The Chinese markets exhibited daily and monthly calendar effects, higher returns were observed on Fridays and in the months of March and April.

Golaka C Nath *et al*., (2005) studied the day of the week effect and market efficiency of NSE for the period 1999-2003. The study found that prior to the introduction of rolling settlement in the year 2002, the days Monday and Friday were significant. Friday became significant after the introduction of rolling settlement. Mondays were found to have higher standard deviations followed by Fridays. Market inefficiency existed according to the findings of the study.

Srividya *et al*.,(2010) in their study of monthly returns for 132 closing prices of BSE Sensitive Index to test seasonality of stock returns showed that the coefficient for the month of December was found to be statistically significant. Autocorrelation Function (ACF) and ARIMA (Autoregressive Integrated Moving Average) models were used to test seasonality of stock returns. The results of the study indicate that the stock returns in India are not entirely random and stock market may not be informationally efficient.

Sarbapriya Ray (2012) in the study investigated the existence of seasonality in stock returns in Bombay Stock Exchange (BSE) sensex. The author used monthly closing share price data of the Bombay Stock Exchange's share price index from January, 1991 to December, 2010 for this purpose. Using a combined regression –time series model with dummy variables for months, existence of seasonality in stock returns was tested. The results of the study provide 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'. The findings have important implications for the financial managers, financial analysts and investors. The understanding of seasonality would help them to develop appropriate investment strategies.

Shahid Ali *et al*., (2012) investigated calendar anomalies in the Pakistani stock market by taking a data of stock returns of fifteen years from November 1991 to October 2006. Using one Factor ANOVA the main hypotheses about equality in returns on daily, weekly and monthly basis were tested using F-test and are found to be insignificant, Autoregressive Integrated Moving Averages (ARIMA) and Ordinary Least Squares (OLS) are also extended as an alternate procedure to look for any above average returns reaped by market players. An AR(1) model is fitted on the data along with a simple linear regression model to test the slopes. The authors examined the residuals to find evidence of serial correlation using the Durbin-Watson statistic. Anderson-Darling test of normality is applied as a prerequisite before computing interval estimates and using the one factor ANOVA. The study concludes that there are no weekly effects or monthly effects in stock returns in Pakistani equity market however the market is inefficient in the short run and there is existence of daily effects where the fourth and fifty days of a week show abnormal returns using autoregressive modeling.

3. Objectives

The following are the objectives of the study:

To assess the presence of seasonal or monthly effect of stock returns for the period of study.

To study the presence of month of the year effect of stock returns of BSE sensex

4. Methodology

Monthly data of BSE sensex data from April 2004 to March 2012 were taken from www.bseindia.com. In examining seasonality in the ECMs, most studies adopted the methodology similar to the study of the developed stock markets (Keim, 1983; Kato and Schallheim, 1985; Jaffe and Westerfield, 1989). Most of the studies carried out using the above said methodology may fail to actually predict the seasonal effect in the series as they do not shed light on basic characteristics of time series data such as normality, autocorrelation, heteroskedasticity etc.

Hence the objective of this study is to develop an effective approach as explained below. In this study, a more robust approach is followed which is discussed below.

The monthly return of the BSE sensex for the period starting from April 2004 to March 2012 is calculated as natural logarithm of the ratio between the current period index(Y_t) and previous period share index $Y_{(t-1)}$.

The formula is:

$$r_t = l_n\left(Y_t \mid Y_{t-1}\right) \qquad (1)$$

where r_t is the return in the period t, Y_t is the monthly average share price of the Sensex for the period t, Y_{t-1} is the monthly average share price of the Sensex for the period t-1 and ln natural logarithm.

After finding the return, the first step is to check for the normality of the return using the summary statistics like Arithmetic mean, Median, Skewness, Kurtosis and Jarque-Bera test. If the Mean and Median are approximately equal, Skewness is zero, Kurtosis is around three and if the Jarque-Bera values is significant, then it is interpreted that the series follow normal distribution.

In order to test the stationarity of the data, Augmented Dickey-Fuller (ADF) test is used where the null hypothesis is that the series have unit root. Following equation checks the stationarity of time series data used in the study:

$$\Delta r_t = \mu + (\alpha - 1)\, r_{t-1} + \sum\nolimits_{i=1}^{p} \alpha_i \,\Delta r_{t-1} + \varepsilon_t \qquad (2)$$

Where ε_t is white noise error term in the model of unit root test, with a null hypothesis that return has unit root at time t. The test for a unit root is conducted on the coefficient of r_{t-1} in the regression. If the coefficient is significantly different from zero (less than zero) then the null hypothesis is rejected.

The null and alternative hypothesis for the existence of unit root in variable r_t is

$$H0;\ \alpha = 0 \text{ versus } H1:\ \alpha < 0.$$

Rejection of the null hypothesis denotes stationarity in the series. The unit root test tests for the existence of a unit root in two cases: with intercept only and with intercept and trend to take into the account the impact of the trend on the series.

Stationarity of the return series can be determined using the Autocorrelation function (ACF) and Partial Auto correlation Function (PACF). Tintner defines autocorrelation as "lag correlation of a given series with itself, lagged by a number of time units". The autocorrelation at lag t by rt is given by

$$rt = \frac{\sum_{i=k+1}^{n}\left(Y_i - \bar{Y}\right)\left(y_{i-k} - \bar{Y}\right)}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2} \qquad (3)$$

Together, the autocorrelations at lags 1, 2,…. make up the autocorrelation function(ACF). When the autocorrelations are plotted against the lags, gives the correlogram. It also helps to check for cycles and other time series patterns.

The estimated Partial Autocorrelation function is used as a guide along with the estimated autocorrelation function ACF, in choosing one or more ARIMA models that might fit the available data. The idea of partial correlation analysis is that one want to measure how r_t and r_{t+k} are related , when the effects of other time lags 1, 2, ….k-1 are removed. The partial autocorrelation of order k is denoted by αk and can be calculated by regressing r_t against $r_{t-1}, \ldots r_{t-k}$.

$$R_t = b_o + b_1 r_{t-1} + b_2 r_{t-2} + \ldots\ b_k r_{t-k} \qquad (4)$$

If the ACF and PACF coefficient lie with in the critical values, ±1.96(1/N), then the return is white noise. If the ACF coefficient falls outside the critical indicates that there is some seasonality in the forecast errors and the forecast method could be improved. The ACF and PACF help to find the number of lags to be considered in the AR process.

The Ordinary Least Square method is used to find the

Table 1: Summary Statistics - MonthWise

	JAN	*FEB*	*MAR*	*APR*	*MAY*	*JUN*	*JUL*	*AUG*	*SEP*	*OCT*	*NOV*	*DEC*	*Return*
Mean	-0.0243	-0.0129	0.0472	0.0343	-0.0082	0.0010	0.0147	0.0434	0.0106	-0.0207	0.0141	-4.32E-	0.0082
Median	-0.0224	-0.0202	0.0216	0.0140	0.0155	-0.0002	0.0295	0.0622	0.0399	-0.0169	0.0200	-0.0035	0.0106
Maximum	0.0325	0.0909	0.2129	0.1956	0.1330	0.0641	0.0733	0.1167	0.1529	0.0616	0.0506	0.1124	0.2129
Minimum	-0.0826	-0.1066	-0.0159	-0.0349	-0.1434	-0.0854	-0.0835	-0.0529	-0.2433	-0.1038	-0.0414	-0.1063	-0.2433
Std. Dev.	0.0433	0.0806	0.0843	0.0869	0.1035	0.0577	0.0631	0.0638	0.1349	0.0669	0.0310	0.0716	0.0757
Skewness	-0.0641	0.1610	1.5011	1.1532	-0.1352	-0.2364	-0.5343	-0.5009	-1.1709	-0.0737	-0.8761	0.1317	-0.1713
Kurtosis	1.7431	1.5683	3.6887	3.0439	1.8204	1.8879	1.8424	1.8611	3.3180	1.5616	2.9428	2.6302	4.2848
Jarque-Bera	0.3990	0.5383	2.3721	1.3305	0.3661	0.3650	0.6205	0.5752	1.3964	0.5226	0.7683	0.0515	5.3048
Probability	0.8191	0.7640	0.5418	0.5141	0.8327	0.8331	0.7332	0.7500	0.4974	0.7700	0.6810	0.9745	0.0704
Sum	-0.1460	-0.0778	0.2837	0.2060	-0.0496	0.0064	0.0885	0.2607	0.0636	-0.1244	0.0850	-0.0002	0.5958
Sum Sq. Dev.	0.009	0.032485	0.035574	0.037824	0.053605	0.016700	0.019909	0.020398	0.091120	0.022386	0.004825	0.025682	0.407574
Observations	6	6	6	6	6	6	6	6	6	6	6	6	72

month of the year effect in the return series. To estimate the OLS we introduce the 12 monthly dummy variables each for January till December where in each dummy variable 1 represents the corresponding month and 0 represents the rest. To run OLS we set January as the benchmark (January effect).

$$r_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t$$

Hence in OLS equation the constant represents the average of January month. The other coefficients are the difference in the average return between January and the corresponding month. If the coefficient is significant, then that particular month is significantly different from January.

In this model ε_t is the residual which may be autocorrelated. Hence to improve the this model we construct the ARIMA(p,d,q) model. The AR and MA models may be revealed – the pattern of autocorrelation and partial autocorrelation will indicate a possible model. If there are no significant autocorrelation after lag q, a MA(q) model may be appropriate. If there are no significant partial autocorrelations after lag p, an AR(p) model may be appropriate. Then one can introduce the ARIMA(p,d,q) in the OLS equation to deal with the stochastic term ε_t.

The transfer function model (Pandey, 2002 & Lazar *et al*, 2005 use similar model) is as follows:

$$y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varphi -1(B)\theta(B)\eta_t \quad (5)$$

where η_t is a normally distributed error term and it may have different variance from ε_t. In this model the residual is tested for white noise (ARCH Effect) using Box-Pierce Q statistics. In this research there is no ARCH effect.

5. Result and Analysis

5.1 Normality

Table 1 gives the month wise summary statistics of the return series. The months January, February , May, October and December have negative average returns. table 1 also shows the median, maximum, minimum and standard deviation (risk) of the return series. Except for the months March, April, May and December the other months' returns are negatively skewed(<0). March, April and September show slightly leptokurtic curve (Kurtosis >0). The normality of the data can be well defined and easily identified using Jarque - Bera test. From the p-value (>0.05) of Jarque – Bera Test it is found that the monthly average return and the overall return follow normal distribution

5.2 Stationarity

To test the stationarity ADF test is performed. In table 2, the ADF test statistics is significant at 1% level and hence the null hypothesis is rejected. Therefore, the returns does not have unit root and the series is stationary. It is also evident from the ACF and PACF below.

Table 2: Augmented Dickey Fuller Test

Null Hypothesis: RETURNS has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic based on SIC, MAXLAG=32)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-6.275521	0.0000
Test critical values:	1% level		-3.525618	
	5% level		-2.902953	
	10% level		-2.588902	
*MacKinnon (1996) one-sided p-values.				

5.3 Seasonality

Figure 1 shows the correlogram of autocorrelation function and partial autocorrelation function. The 95% of the ACF and PACF lie between the limits $\pm 1.96/\sqrt{n}$. Hence the series is stationary. Also there is less evidence of seasonality.

5.4 Month of the Year Effect

Table 3 shows the OLS model to find the month of the year effect. It is found that since January is taken as benchmark, the constant term is equal to the average return of January. The other coefficients are the different between the corresponding month and January. All the coefficients of dummy variables are insignificant. Hence no month's return is significantly different from January. Also the independent variables explain only 0.83% (R2

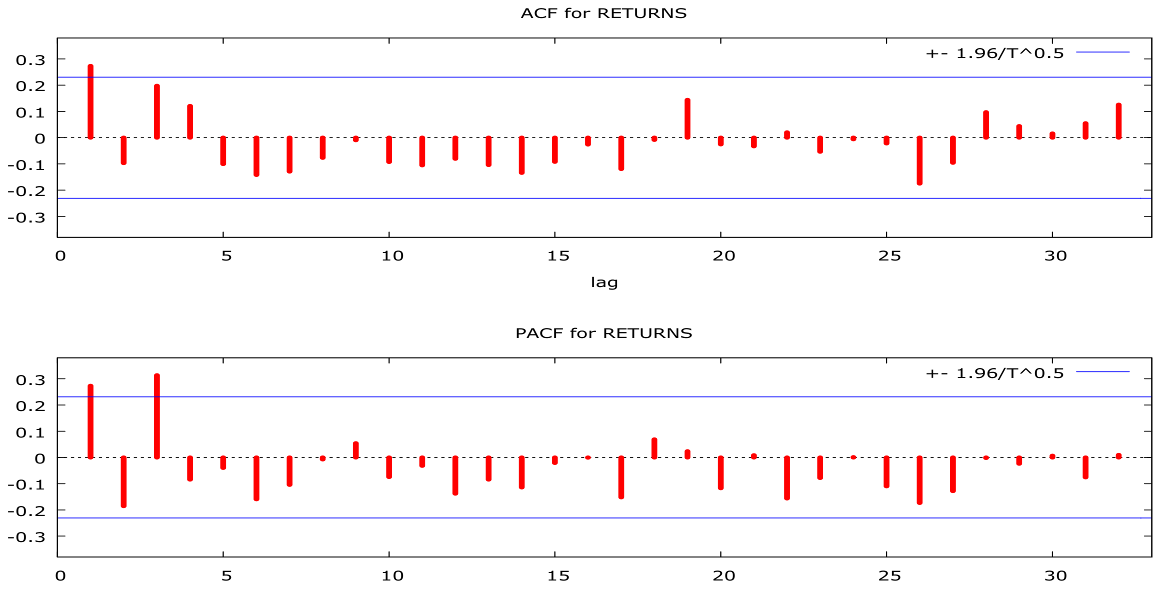

Figure 1: Correlogram of ACF and PACF

Table 3: Ordinary Least Square Method to Test Seasonality

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	*Sig*
Const	-0.0243475	0.0320558	-0.7595	0.45051	Not Significant
D_{Feb}	0.0113673	0.0453337	0.2507	0.80287	Not Significant
D_{Mar}	0.0716398	0.0453337	1.5803	0.11930	Not Significant
D_{Apr}	0.0586855	0.0453337	1.2945	0.20045	Not Significant
D_{May}	0.016069	0.0453337	0.3545	0.72424	Not Significant
D_{Jun}	0.0254177	0.0453337	0.5607	0.57710	Not Significant
D_{Jul}	0.039105	0.0453337	0.8626	0.39179	Not Significant
D_{Aug}	0.0678013	0.0453337	1.4956	0.14000	Not Significant
D_{Sep}	0.0349485	0.0453337	0.7709	0.44378	Not Significant
D_{Oct}	0.00360465	0.0453337	0.0795	0.93689	Not Significant
D_{Nov}	0.0385308	0.0453337	0.8499	0.39874	Not Significant
D_{Dec}	0.0243043	0.0453337	0.5361	0.59386	Not Significant

Mean dependent var	*0.008275*		*S.D. dependent var*	*0.075766*
Sum squared resid	0.369926		S.E. of regression	0.078520
R-squared	0.092371		Adjusted R-squared	-0.074027
F(11, 60)	0.555121		P-value(F)	0.856847
Log-likelihood	87.59672		Akaike criterion	-151.1934
Schwarz criterion	-123.8734		Hannan-Quinn	-140.3173
Rho	0.284337		Durbin-Watson	1.422308

= 0.008275) of variation in the average returns, which is very low. Insignificant F (0.555) also shows that the model is not a good fit. Durbin Watson value 1.422 is also less than 2 hence there is an evidence for autocorrelation between the residuals of the model.

5.5 Residual Test

To test the nature of the residuals in the OLS model, Breusch-Godfrey Serial Correlation LM Test is performed. The significance of the F statistics in Table 4 shows that there is serial correlation between the residuals. Also the Durbin Watson 1.88 shows that there is autocorrelation between the residuals.

5.6 Autoregressive Moving Average Model (ARMA)

As there are evidences of autocorrelation between the residuals in the OLS model constructed, the model needs improvement. Hence the ARIMA(p,d,q) model is constructed and the values p,q and d are to be determined. Based on the correlogram of ACF and PACF it is evident that there is significant correlation in the first and third lag. Hence the AR(1) and MA(1) process are chosen. Autoregressive AR model can be efficiently coupled with Moving Average Models (MA) to form a general and useful class of time series models called ARMA model. However they can be only used if the data are stationary.

Table 5 gives the ARMA(1,1) model for the data. The model seems to be a good model as the AR(1) coefficient and MA(1) coefficient are significant (<0.05). Also the R square value is 0.2492, i.e it explain 24% of the variation. No further improvement is needed as the Adjusted R square 0.2271 is less than the R square which implies that addition of one more variable reduces the explanatory power of the model. The validity of the model can also tested using the unit roots.

Then the ARIMA(p,d,q) is introduced in the OLS equation to deal with the stochastic term ε_t. Table 6 gives the transfer function model.

The model fit is determined to be good with the help of R square value (0.3811) and Adjusted R square (0.24 < R square). The significance level of the F statistics also proves the model fit. The DO_{ct} representing the October

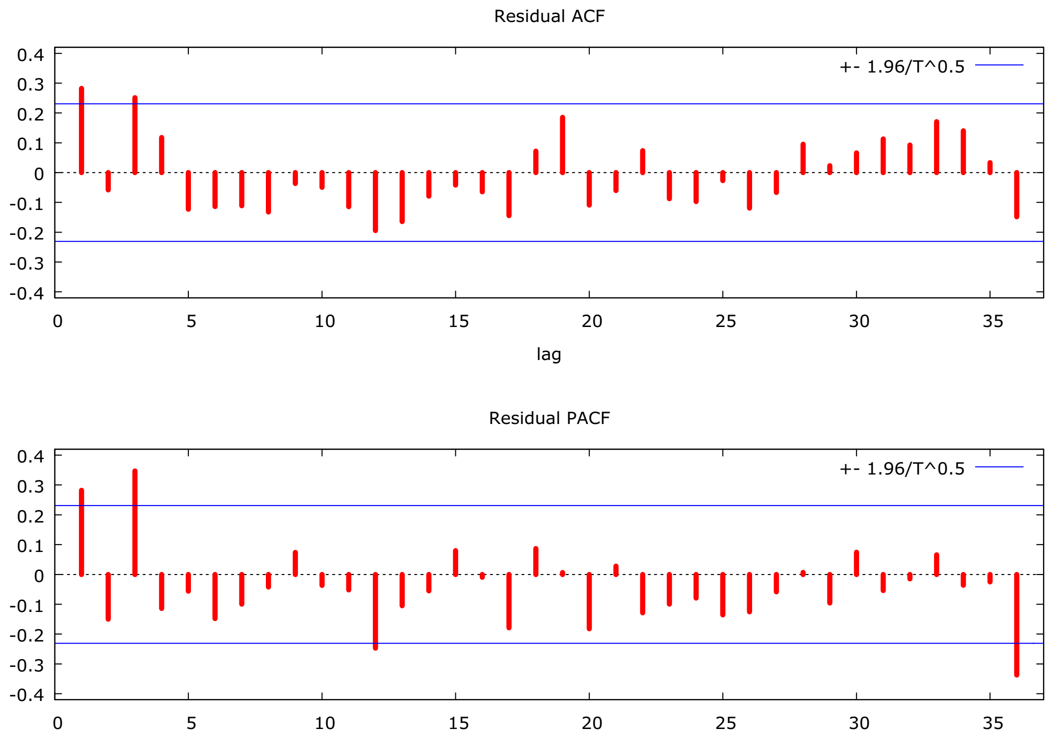

Figure 2: Residual ACF and PACF Correlogram

Table 4: Test for Autocorrelation in the Residuals

Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	3.268495	Prob. F(2,58)		0.0452
Obs*R-squared	7.292922	Prob. Chi-Square(2)		0.0261
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.17E-16	0.030908	3.77E-15	1.0000
D_{Feb}	-1.60E-16	0.043711	-3.66E-15	1.0000
D_{Mar}	-9.69E-17	0.043711	-2.22E-15	1.0000
D_{Apr}	-0.002683	0.043725	-0.061353	0.9513
D_{May}	0.001319	0.043726	0.030155	0.9760
D_{Jun}	-1.22E-16	0.043711	-2.78E-15	1.0000
D_{Jul}	-1.15E-16	0.043711	-2.62E-15	1.0000
D_{Aug}	-1.40E-16	0.043711	-3.21E-15	1.0000
D_{Sep}	-1.18E-16	0.043711	-2.70E-15	1.0000
D_{Oct}	-1.17E-16	0.043711	-2.67E-15	1.0000
D_{Nov}	-1.21E-16	0.043711	-2.78E-15	1.0000
D_{Dec}	-1.22E-16	0.043711	-2.80E-15	1.0000
RESID(-1)	0.327670	0.130370	2.513386	0.0148
RESID(-2)	-0.151562	0.130379	-1.162471	0.2498
R-squared	0.101291	Mean dependent var		7.42E-18
Adjusted R-squared	-0.100144	S.D. dependent var		0.072182
S.E. of regression	0.075710	Akaike info criterion		-2.151149
Sum squared resid	0.332456	Schwarz criterion		-1.708464
Log likelihood	91.44136	Hannan-Quinn criter.		-1.974915
F-statistic	0.502845	Durbin-Watson stat		1.884533
Prob(F-statistic)	0.913867			

Table 5: ARMA(1,1) Model

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	0.009082	0.010966	0.828138	0.4105
AR(1)	-0.322294	0.156469	-2.059799	0.0432
MA(1)	0.825029	0.093265	8.846109	0.0000
R-squared	0.249203	Mean dependent var		0.008563
Adjusted R-squared	0.227121	S.D. dependent var		0.076266
S.E. of regression	0.067048	Akaike info criterion		-2.525487
Sum squared resid	0.305688	Schwarz criterion		-2.429881
Log likelihood	92.65480	Hannan-Quinn criter.		-2.487468
F-statistic	11.28524	Durbin-Watson stat		2.037544
Prob(F-statistic)	0.000059			
Characteristic Roots		Real		
AR	Root 1	-2.8325		
MA	Root 1	-1.2411		

Table 6: Introducing ARMA(1,1) in the OLS equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.024333	0.032141	-0.757053	0.4521
D_{Feb}	0.011346	0.037956	0.298935	0.7661
D_{Mar}	0.069450	0.048055	1.445222	0.1539
D_{Apr}	0.059612	0.046072	1.293898	0.2009
D_{May}	0.041772	0.046709	0.894292	0.3749
D_{Jun}	0.015269	0.045410	0.336249	0.7379
D_{Jul}	0.043083	0.045637	0.944036	0.3491
D_{Aug}	0.066213	0.045282	1.462241	0.1492
D_{Sep}	0.035554	0.045888	0.774790	0.4417
D_{Oct}	0.003345	0.044371	0.075396	0.9402
D_{Nov}	0.038612	0.048090	0.802907	0.4254
D_{Dec}	0.024251	0.037956	0.638927	0.5254
AR(1)	-0.394037	0.114564	-3.439439	0.0011
MA(1)	0.976967	0.013197	74.02749	0.0000
R-squared	0.381168	Mean dependent var		0.008563
Adjusted R-squared	0.240031	S.D. dependent var		0.076266
S.E. of regression	0.066485	Akaike info criterion		-2.408930
Sum squared resid	0.251958	Schwarz criterion		-1.962767
Log likelihood	99.51700	Hannan-Quinn criter.		-2.231505
F-statistic	2.700696	Durbin-Watson stat		2.024486
Prob(F-statistic)	0.004971			
AR	Root 1	-2.0082	AR	Root 1
MA	Root 1	-1.0000	MA	Root 1

month has the highest significant value which says that the average return is approximately equal to January's average return.

The Durbin Watson value 2.0244 (>=2) implies that there is no auto correlation in the residual series. To test for the heteroscedasticity of the model, ARCH test is conducted. The null hypothesis is that there is no no ARCH effect is present. The test statistics is LM = 9.4028, and the significance level is 0.668195. Hence there is no ARCH effect in the transferred model equation.

6. Findings and Conclusion

The study using the summary statistics has found that the maximum returns occur in the month of March and the minimum returns also occur in the month of March. The study also finds that the returns are positive for seven months and negative for five months. From Table 6, it is found that the average returns for the benchmark returns (Janauary) is (2.43)% and none of the coefficients of all the months are statistically significant thus concluding that there is no presence of seasonality in the sensex returns. This despite the fact of the model being fit and statistically significant. The results do not confirm the presence of January effect. Tax-selling hypothesis also do not hold good for the selected period of study of BSE Sensex. The study also finds that stock market may be informationally efficient. Based on the present study, the investors can use the coefficient values of the respective months to trade in securities. The investors can buy in the month of Februrary(lowest returns) and sell in the month of March. Further research is required to test the seasonality of index returns. Future studies can focus on 'Day of the Week' effect because of the introduction of rolling settlement in India in the year 2002. By analyzing the Day of the Week effect, better understanding can be derived regarding the seasonality of index returns which in turn may help the investors devise better strategies for improved returns.

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