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Investigating Seasonal Behavior in the Monthly Stock Returns: Evidence from BSE Sensex of India

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Abstract: Increasing globalization of the financial markets and the flawless nature of cross border investment flows have sharpened interest in emerging markets. Due to the structural changes, globalization of the capital markets, and internationalization of the world economy, growing attention is being given to emerging capital market. There are reports and studies both in India and abroad on the seasonality of the Sensex monthly returns. The objective of the study is to investigate the existence of seasonality in stock returns in Bombay Stock Exchange (BSE) sensex.We use monthly closing share price data of the Bombay Stock Exchange's share price index from January,1991 to December,2010for this purpose. We use a combined regression –time series model with dummy variables for months to test the existence of seasonality in stock returns. 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'. These findings have important implications for the financial managers, financial analysts and investors. The understanding of seasonality would help them to develop appropriate investment strategies.

Key words: Seasonality, market efficiency, efficient market hypothesis, tax-loss selling hypothesis, monthly stock returns, stationarity, BSE.

JEL Classification: G11, G12, G14.

1. Introduction

Increasing globalization of the financial markets and the flawless nature of cross border investment flows has sharpened interest in emerging markets. Due to the structural changes, globalization of the capital markets, and internationalization of the world economy, growing attention is being given to emerging capital market. There are studies which have examined the seasonality of stock returns in emerging capital markets. Seasonality refers to regular and repetitive fluctuation in a time series which occurs periodically over a span of less than a year. The main cause of seasonal variations in time series data is the change in climate. Stock returns exhibits systematic patterns at certain times of the day, week or month. The most common of these are monthly patterns; certain months provide better returns as compared to others i.e. the month of the year effect. Similarly, some days of the week provide lower returns as compared to other trading days i.e. days of the week effect. The existence of seasonality in stock returns however violates an important hypothesis in finance that is efficient market hypothesis. The efficient market hypothesis is a central paradigm in finance.

According to the Efficient Market hypothesis, past prices of shares should have no predictive power of future prices. In effect, prices should be random. However, numerous studies have been carried to prove that market inefficiencies do exist and that anomalies may be in terms of seasonal effects over the day of the week, the months of the year or over specific years. For instance, the months of year effect would exist if returns on a particular month are higher than other months. This will negate the notion of efficiency in markets since traders will be able to earn abnormal returns just by examining patterns monthly returns and setting trading strategies accordingly. Essentially, this will entail an inefficient market situation where returns are not proportionate with risk. The Efficient Market hypothesis (EMH) relates to how quickly and accurately the market reacts to new information. New data are constantly entering the market place via economic reports, company announcements, political statements, or public surveys. If the market is informationally efficient then security prices adjust rapidly and accurately to new information. According to this hypothesis, security prices reflect fully all the information that is available in the market. Since all the information is already incorporated in prices, a trader is not able to make any excess returns. Thus, EMH proposes that it is not possible to outperform the market through market timing or stock selection. However, in the context of financial markets and particularly in the case of equity market seasonal component have been recorded. They are called calendar anomalies (effects) in literature.

Therefore, 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.

The existence of seasonality in stock returns violates the weak form of market efficiency because equity prices are no longer random and can be predicted based on past pattern. This facilitates market participants to devise trading strategy which could fetch abnormal profits on the basis of past pattern. For instance, if there are evidences of 'day of the week effect', investors may devise a trading strategy of selling securities on Fridays and buying on Mondays in order to make excess profits. Aggarwal and Tandon (1994) and Mills and Coutts (1995) pointed out that mean stock returns were unusually high on Fridays and low on Mondays. One of the explanations put forward for the existence of seasonality in stock returns is the 'tax-loss-selling hypothesis. In the USA, December is the tax month. Thus, the financial houses sell shares whose values have fallen to book losses to reduce their taxes. As of result of this selling, stock prices decline. However, as soon as the December ends, people start acquiring shares and as a result stock prices bounce back. This lead to higher returns in the beginning of the year, that is, January month. This is called 'January effect'. In India, March is the tax month; it would be interesting to find 'April Effect'.

1.1. Brief Review of Existing literature on seasonality of stock returns

Several studies have investigated the seasonal behavior of monthly stock market returns of a number of countries. But most of the studies were conducted on developed countries. The "January effect" and the "tax-loss –selling" hypotheses are two important hypothesis tested in the literature. The seasonality would exist in stock returns if the average returns were not same in all periods. The month-of –the year effect would be present when returns in some months are higher than other months. There are empirical studies which have found the 'year end' effect and 'January effect' in stock returns consistent with the 'tax-loss selling hypothesis. In order to have tax benefit, the investors sell shares towards the end of the year, which would bring down the stock prices. It is argued that investors sell shares the values of which have declined in order to reduce their taxes. This put a downward pressure on the stock prices and thus lowers stock returns. Soon after this, investors start buying shares and stock prices bounce back. This makes higher returns in the beginning of the year, that is, in the month of January. This year-end effect and January effects are true for the countries like USA whose tax period ends in December. Whereas country like India has different tax period, namely, it starts from April of the year and ends on March of next year. If the same logic is applied to Indian data, it is expected to have April effect as if investors sell shares during March to save tax.

Literature also flourishes 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. Since the seminal work of Fama (1965), a vast number of studies have been developed regarding security price anomalies. Some of them are broadly known as calendar effects. The most important calendar effects studied are the day of the week effect (significantly different returns on some day of the week; usually higher Friday returns and lower Monday returns), the monthly (or January) effect (relatively higher January returns), the half month effect (returns are statistically higher over the first half of the month), the turn of the month (statistically higher returns on turn of the month days than other trading days) and the time of the month effect (returns are higher on the first third of the month). Wachtel (1942) first pointed out the seasonal effect in the US markets.

Rozeff and Kinney (1976) documented that average stock returns in January are higher than any other month and found that stock returns in January were statistically larger than in other months.

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.

Keim (1983) examined 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. Reinganum (1983), however, found that the tax-loss-selling hypothesis could not explain the entire seasonality effect.

Gultekin and Gultekin (1983) confirmed the January effect after studying data of 17 industrial countries with different tax laws.

DeBondt and Thaler (1985) found 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.

Smirlock and Starks (1986) found evidence of the day-of the- week effect and Ariel (1987) found intra-month effects in the US stock returns. Chan (1986) found that the source of January seasonal in stock returns is long-term loss.

In many others developed countries similar type of study had been done on the seasonality. The existence of seasonal effect has been found in Australia (Officer, 1975;Brown, Keim, Kleidon and Marsh, 1983), the UK (Lewis, 1989), Canada (Bergers, McConnell, and Schlarbaum, 1984; Tinic, Barone-Adesi and West, 1990) and Japan (Aggarwal, Rao and Hiraki, 1990). Boudreaux (1995) reported the presence of the month-end effect in markets in Denmark, Germany and Norway. Jaffe and Westterfield (1989) found a weak monthly effect in stock returns on many countries.

Very few studies have revealed the presence of seasonal effect of stock returns for the emerging capital market (Aggarwal and Rivoli, 1989; Ho, 1990; Lee Pettit and Swankoski, 1990; Lee, 1992; Ho and Cheung, 1994; Kamath, Chakornpipat, and Chatrath, 1998; and Islam, Duangploy and Sitchawat, 2002). Ramachanran (1997) has rejected the seasonal effect for the stock market in Jamaica.

Raj and Thurston (1994) investigated the January and April effects in the NZ stock market but found no significant effect.

Pandey (2002) examined the Bombay Stock Exchange's benchmark index `Sensex' for the period 1991 to 2002 and confirmed 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 replacing the residuals with an ARIMA model.

Maghyereh (2003) using the standard GARCH, exponential GARCH (EGARCH) and the GJR models for Amman Stock Exchange (ASE) of Jordan found no evidence of monthly seasonality as well as January effect in the ASE returns.

Brown and Luo (2004)studying data from NYSE equal weighted stock index for the period of 1941 to 2002 introduces a new type of January effect, namely the signs of January returns have superior predictive value vis-a-vis the signs of any other calendar month's returns for the purpose of predicting the next 12-months' returns.

Lazar et al.(2005) using data from Bombay Stock Exchange’s Sensitivity Index document the monthly effect in the stock returns in India. Their results confirm the existence of seasonality in stock returns in India consistent with the ‘tax-loss selling’ hypothesis.

Alagidede and Panagiotidis (2006) examined both the day of the week and month of the year in the stock returns in Ghana employing rolling techniques to asses the affects of policy and institutional changes thereby allowing deviations from the linear paradigm. Contrary to a January return pattern in most markets, they find an April effect for Ghana’s stock market.

Doran et al.(2008) find using data form Chinese stock markets find that Chinese stock markets as a whole and highly volatile Chinese stocks in particular outperform at the turn of the Chinese New Year, but not in January.

In this study, we extend the investigation of the monthly effect in stock returns for the Indian stock market for the post reform period, 1991-2010.

In view of the above discussion, the objective of the study is to investigate the existence of seasonality in stock returns in Bombay Stock Exchange (BSE) sensex. We use monthly closing share price data of the BSE share price index from January,1991 to December,2010for this purpose. We use a combined regression –time series model with dummy variables for months to test the existence of seasonality in stock returns.

Therefore, this study specified an autoregressive integrated moving average model with dummy variables for months to investigate the existence of seasonality in stock returns in BSE. The results of the study confirmed the monthly effect in stock returns in India and also supported the ‘tax-loss selling’ hypothesis.

The structure of the article is as follows: section 2 describes the brief overview on Bombay Stock Exchange and section 3 presents methodological issues and data base; analytical results are presented in section4 and section 5 presents concluding remarks.

2. Overview of the Bombay Stock Exchange

The Bombay Stock Exchange, which started in 1875 as “The Native Share and Stockbrokers Association” is the oldest exchange in Asia, predating the Tokyo Stock Exchange by 3 years. For the better part of its existence it held a preeminent position as a monopolistic institution for security trading in India. More recently its position has been challenged by the National Stock Exchange (NSE) an online electronic exchange which was established in 1994. It is therefore not surprising that this monopolistic position of the BSE has led to dubious practices, resulting in lack of transparency, high transaction costs and poor liquidity. Over 7000 stocks are listed at the BSE, (of these, about 1300 are cross listed at the newly formed NSE). Whereas, almost 100% of trading used to take place at the BSE, its share has fallen to about 35% in recent years. There is no organized source of price data for all the securities that trade on the BSE. What is collected and disseminated by the BSE is a 30 stock index called the Bombay Sensitive Index, popularly referred to as the Sensex. The stocks included in the Sensex account for about 38% to 40% of the capitalization of all stocks listed at the exchange. Along with overall financial reforms in the Indian financial sector, the BSE also has undergone some changes in recent years, notably the introduction of its online trading system (BOLT), presumably aimed at dealing with the increased competition from the newcomer on the block – the NSE. The total market capitalization of the BSE market is estimated at 3.8 trillion Indian rupees (approximately US$ 82), about 38% of which is represented by the 30 stocks of the Sensex.

3. Methodology& Data database

The monthly data on BSE sensex for the period January, 1991 to December, 2010 obtained from the Handbook of Statistics on Indian Economy and Handbook of Statistics on Indian Security Market published by the Reserve Bank of India.

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). The methodologies of a number of studies have been criticized as they fail to handle the issues of normality, autocorrelation, heteroskedasticity etc. In this study, we follow a more robust approach as discussed below.

The seasonal effect is straightforwardly detectable in the market indices or large portfolios of shares rather than in individual shares (Boudreaux, 1995). This study analyses monthly returns of the DSE All Index from 1991 to 2010. We measure stock return as the continuously compounded monthly percentage change in the share price index as shown below:

$r_t = (\ln P_t - \ln P_{t-1}) \times 100$ --------------------------(1)

where r_t is the return in the period t, Pt is the monthly average share price of the Sensex for the period t and ln natural logarithm.

We first determine whether the BSE return series is stationary. One simple way of determining whether a series is stationary is to examine the sample autocorrelation function (ACF) and the partial autocorrelation function (PACF). In time series analysis, the partial autocorrelation function (PACF) plays a crucial role in data analyses which aimed at identifying the extent of the lag in an autoregressive model. The use of this function was introduced as part of the Box-Jenkins approach to time series modeling, where by plotting the partial autocorrelative functions one could determine the appropriate lags p in an AR(p) model or in an extended ARIMA(p,d,q) model. The Ljung–Box test (named for Greta M. Ljung and George E. P. Box) is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags, and is therefore a portmanteau test. The Ljung–Box test is commonly used in autoregressive integrated moving average (ARIMA) modeling. Note that it is applied to the residuals of a fitted ARIMA model, not the original series, and in such applications the hypothesis actually being tested is that the residuals from the ARIMA model have no autocorrelation. When testing ARIMA models, no adjustment to the test statistic or to the critical region of the test are made in relation to the structure of the ARIMA model.

We also use a formal test of stationarity, that is, the Augmented Dickey-Fuller (ADF) test and Phillips- Perron (PP) Test. To test the stationary of variables, we use the Augmented Dickey Fuller (ADF) test which is mostly used to test for unit root. Following equation checks the stationarity of time series data used in the study:

$$\Delta y_t = \beta_1 + \beta_1 t + \alpha y_{t-1} + \gamma \sum_{t=1}^{n} \Delta y_{t-1} + \varepsilon_t \text{ ------(2)}$$

Where ε_t is white nose error term in the model of unit root test, with a null hypothesis that variable has unit root. The ADF regression test for the existence of unit root of y_t that represents all variables (in the natural logarithmic form) at time t. The test for a unit root is conducted on the coefficient of y_{t-1} in the regression. If the coefficient is significantly different from zero (less than zero) then the hypothesis that y contains a unit root is rejected. The null and alternative hypothesis for the existence of unit root in variable y_t is H0; $\alpha = 0$ versus H1: $\alpha < 0$. Rejection of the null hypothesis denotes stationarity in the series.

If the ADF test-statistic (t-statistic) is less (in the absolute value) than the Mackinnon critical t-values, the null hypothesis of a unit root can not be rejected for the time series and hence, one can conclude that the series is non-stationary at their levels. 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.

The PP tests are non-parametric unit root tests that are modified so that serial correlation does not affect their asymptotic distribution. PP tests reveal that all variables are integrated of order one with and without linear trends, and with or without intercept terms.

Phillips–Perron test (named after Peter C. B. Phillips and Pierre Perron) is a unit root test. That is, it is used in time series_analysis to test the null hypothesis that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis $\delta = 0$ in $\Delta y_t = \delta y_{t-1} + u_t$, here Δ is the first difference operator. Like the augmented Dickey–Fuller test, the Phillips–Perron test addresses the issue that the process generating data for y_t might have a higher order of autocorrelation than is admitted in the test equation - making y_{t-1} endogenous and thus invalidating the Dickey–Fuller t-test. Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of Δy_t as regressors in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation. After a time series has been stationarized by differencing, the next step in fitting an ARIMA model is to determine whether AR or MA terms are needed to correct any autocorrelation that remains in the differenced series.

We will next conduct a test for monthly seasonality in stock returns. We use a month-of-the-year dummy variable for testing monthly seasonality. The dummy variable takes a value of unity for a given month and a value of zero for all other months. We specify an intercept term along with dummy variables for all months except one. The omitted month, that is January, is our benchmark month. Thus the coefficient of each dummy variable measures the incremental effect of that month relative to the benchmark month of January. The existence of seasonal effect will be confirmed when the coefficient of at least one dummy variable is statistically significant.

The existence of seasonal effect will be confirmed when the coefficient of at least one dummy variable is statistically significant (Pandey, 2002). Thus similar to earlier studies, our initial model to test the monthly seasonality is as follows:

$$y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t \text{-------------------------(3)}$$

The intercept term α_1 indicates mean return for the month of January and coefficients $\alpha_2 \ldots \alpha_{12}$ represent the average differences in return between January and each other month. These coefficients should be equal to zero if the return for each month is the same and if there is no seasonal effect. ε_t is the white noise error term. This approach, however, may be flawed because the residuals may have serial correlation.

To deal with this problem, we improve upon Equation (2) by constructing an ARIMA model for the residual series μ_t. We then substitute the ARIMA model for the implicit error term in Equation (2) to form a combined regression –time series model (Pindyck and Rubinfeld, 1998). The transfer function model (Pandey, 2002 & Lazar et al, 2005 use similar model) is as follows:

$$y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varphi^{-1}(B)\theta(B)\eta_t \text{-------------(4)}$$

where η_t is a normally distributed error term and it may have different variance from ε_t.

The last term of equation (4) implies the changed error term due to inclusion of lagged dependent variables and the lagged estimated error terms in ARIMA process. We include lagged dependent variables and lagged error terms in the empirical model. ARCH effect is eliminated by testing the error term for white noise by using Box-Pierce Q statistics. The last term is a theoretical term in equation (4) to represent the lagged dependent variables and the lagged estimated error term, in the ARIMA model (in the original model) in the ARIMA model.

Our data include the closing share price index of the Sensex. The Sensex includes thirty most actively traded shares, and it is a value (market capitalization) weighted share price index. The equal-weighted index places greater weight on small firms and potentially would magnify anomalies related to small firms. Therefore, it is more appropriate to use a value-weighted index to detect the seasonal effect in stock returns. In our analysis, we use monthly returns, calculated by Equation (1), for the period from January, 1991 to December, 2010. This constitutes a sample size of 240 monthly observations. The Indian economy and capital market witnessed significant economic reforms and deregulation after 1991. Therefore, our study covers post-reform period.

4. Analytical Results

Table 1 presents the descriptive statistics for the entire period and each month. There are wide variations across months. Returns for the months of March, May, October and November are negative and the rest of the months have positive mean returns. The maximum average return occurs in the month of September and minimum average returns result in the month of October. Returns for the months of March, April and May are higher than other months. Stock returns show negative skewness for seven months which indicates that flatter tails than the normal distribution. Out of twelve months in a year, four months (March, May, September and October) show leptokurtic (kurtosis>3). The return series for the entire period show high dispersion. Given positive skewness and low kurtosis for many months, the results are as per the expected conditions.

Table 1: Descriptive statistics of the BSE all share price index monthly return (1991-2010)

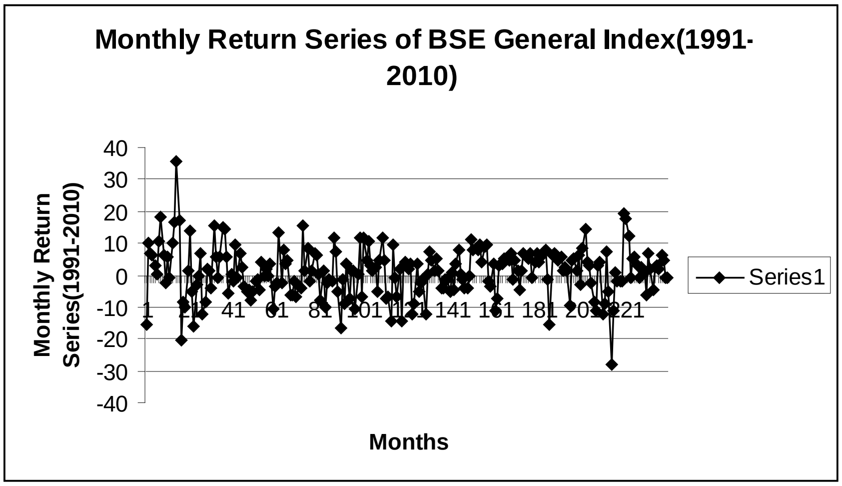
Month	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
Jan.	1.437516	0.674350	15.5662	-15.3563	7.942300	-0.01811	2.763857	0.047563	0.976499	20
Feb.	2.521818	2.474304	16.45135	-8.63187	6.336224	0.353474	2.807101	0.447489	0.799519	20
March.	-0.94476	-2.08795	35.52994	-12.3962	11.17751	1.399709	5.552987	11.96207	0.002526	20
April.	1.603386	1.252719	19.30653	-8.78426	7.859525	0.664807	2.816731	1.501218	0.472079	20
May.	-0.68066	0.747581	17.86995	-20.4616	8.476062	-0.24549	3.695016	0.603428	0.739550	20
June.	0.402492	2.081912	12.49548	-16.48373	8.690075	-0.579604	2.273331	1.559842	0.458442	20
July.	1.122124	-0.32540	10.70484	-9.90633	5.977964	-0.12747	2.185179	0.607437	0.738069	20
Aug.	2.654803	2.493361	17.99575	-9.05716	6.974916	0.354700	2.873426	0.432725	0.805443	20
Sep.	2.726966	4.311761	13.62530	-12.4435	6.090937	-0.84206	3.554428	2.619713	0.269859	20
Oct.	-1.26804	-0.05262	14.23274	-27.8875	8.948750	-1.19367	5.288548	9.114021	0.010493	20
Nov.	-0.68030	2.191739	7.541706	-16.1794	6.897015	-0.79883	2.441485	2.387039	0.303152	20

Dec.	2.366063	1.987914	14.70738	-4.68134	5.114076	0.554591	2.813008	1.054377	0.590262	20

Source: Author's own estimate

Figure 1 gives the plot of the return series which shows variations in monthly returns.

Figure:1



Besides, figure 2 and 3 show the ACF and the PACF of the series. Figure 2 shows that the autocorrelation function falls off quickly as the number of lags increase. This is a typical behaviour in the case of a stationary series. The PACF also does not indicate any large spikes. The steadily declining correlation function implies that the residuals series is stationary.

Figure: 2

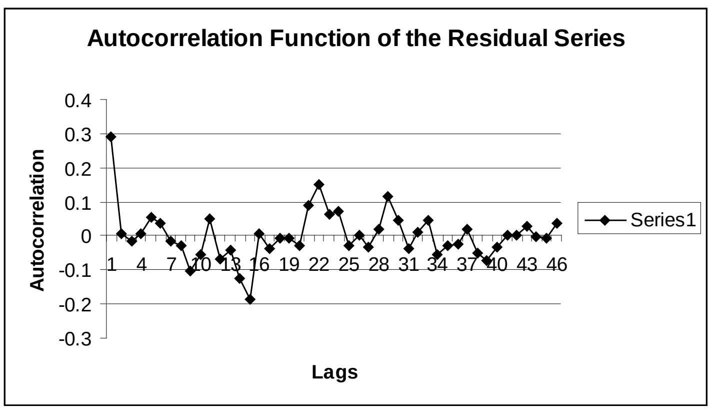


Table 2: Unit Root Test: The Results of the Augmented Dickey Fuller (ADF) Test& Phillips- Perron(PP) Test for Levels with an Intercept and Linear Trend

Augmented Dickey Fuller (ADF) Test	Intercept only			Intercept &Trend		
Variable	ADF(1)	ADF(5)	ADF(10)	ADF(1)	ADF(5)	ADF(10)
BSE Monthly Return	-9.9044	-5.6018	-4.4999	-9.8839	-5.5885	-4.4930
AIC	6.8031	6.8499	6.8717	6.8115	6.8585	6.8798
SBC	6.8469	6.9533	7.0516	6.8698	6.9766	7.0747

	1% Critical Value* -3.4593 5% Critical Value -2.8738 10% Critical Value -2.5732			1% Critical Value* -3.9997 5% Critical Value -3.4299 10% Critical Value -3.1382		
Phillips- Perron(PP) Test						
BSE Monthly Return AIC SBC	-11.6131 6.8137 6.8428	-11.4939 6.8137 6.8428	-11.5019 6.8137 6.8428	-11.5921 6.8216 6.8653	-11.4722 6.8216 6.8653	-11.4811 6.8216 6.8653
	1% Critical Value* -3.4592 5% Critical Value -2.8737 10% Critical Value -2.5732			1% Critical Value* -3.9996 5% Critical Value -3.4298 10% Critical Value -3.1381		

Source: Author's own estimate

Ho: series has unit root; H_1: series is trend stationary.

***MacKinnon critical values for rejection of hypothesis of a unit root.**

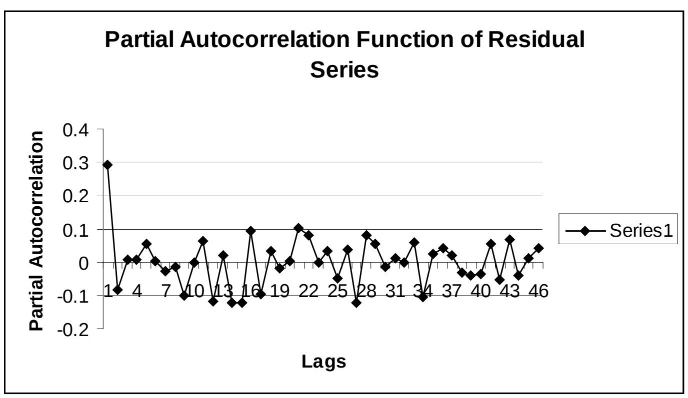
AIC stands for Akaike info criterion

SBC stands for Schwarz Bayesian criterion

#A value greater than the critical t-value indicates non-stationarity.

Table 2 presents the results of the unit root test. The results show that variable of our interest- namely BSE Monthly Return- attained stationarity at level [I(0)]following order 1,5,10 using both augmented Dickey Fuller Test and PP test. The results indicate that the null hypothesis of a unit root can be rejected for the given variable and, hence, one can conclude that the variable - BSE Monthly Return -is stationary at level I(0). The results show consistency with different lag structures and to the presence of the intercept or intercept and trend. Thus the ADF tests also prove that the Sensex return series is stationary.

Figure:3



We estimate Equation (3), which includes the month-of-the-year dummy variables on the right-hand side of the equation. . The results are presented in Table 3.

Table: 3: The Regression Model to Test Seasonality

Variable	**Coefficient**	**Std. Error**	**t-Statistics**	**Prob.**
Constant				
D2 (Feb)	0.211869	0.467414	0.453278	0.6624

D3 (Mar)	-0.263721	0.402830	-0.654671	0.5310
D4 (Apr)	0.620756	0.597438	1.039029	0.3292
D5 (May)	-0.846818	0.411076	-2.060004	0.0734
D6 (Jun)	0.244631	0.343651	0.711858	0.4968
D7 (Jul)	0.305746	0.766833	0.398713	0.7005
D8 (Aug)	-0.133200	0.367506	-0.362442	0.7264
D9 (Sep)	-0.731250	0.683311	-1.070157	0.3158
D10 (Oct)	0.169233	0.322211	0.525224	0.6137
D11 (Nov)	-0.404237	0.673071	-0.600586	0.5647
D12 (Dec)	0.689744	0.834062	0.826969	0.4322
R-squared 0.0931 F-statistic 0.6394 Durbin-Watson stat 1.8289				

Source: Author's own estimate

Only the month of May has statistically significant coefficient. R^2 of 0.0931 is low, and the insignificant F-statistic suggests poor model fit. Durbin-Watson statistic of less than 2 indicates serial correlation in the residuals. The Ljung-Box Q-statistic to order of 46 is 62.11 and it is also significant at 0.057. Thus, the residuals of the model are not white noise. We next examine the residuals obtained from the estimation of Equation (3). After experimenting, we fit the ARIMA (4, 0, 2) model to the residual series and that the residuals of the ARIMA model are white noise.

Table: 4: The Combined Regression-Time Series Model

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Constant	6.20263	1.82639	3.396	0.00068 ***
D2 (Feb)	-0.35170	0.195409	-1.800	0.07189 *
D3 (Mar)	0.183411	0.155099	1.183	0.23699
D4 (Apr)	-0.465932	0.221027	-2.108	0.03503 **
D5 (May)	-0.144313	0.104399	-1.382	0.16687
D6 (Jun)	-0.219539	0.143647	-1.528	0.12643
D7 (Jul)	-0.975324	0.333251	-2.927	0.00343 ***
D8 (Aug)	-0.353381	0.122195	-2.892	0.00383 ***
D9 (Sep)	0.544645	0.177029	3.077	0.00209 ***
D10 (Oct)	0.561978	0.148662	3.780	0.00016 ***
D11 (Nov)	0.294366	0.333103	0.884	0.37685
D12 (Dec)	-0.585851	0.396442	-1.477	0.05590
AR(1)	-1.58300	0.192433	-8.226	<0.00001 ***
AR(2)	-2.30324	0.148105	-15.551	<0.00001 ***
AR(3)	-1.53364	0.185251	-8.279	<0.00001 ***
AR(4)	-0.897704	0.0873163	-10.281	<0.00001 ***
MA(1)	-1.91924	0.231395	-8.294	<0.00001 ***
MA(2)	0.999996	0.212590	4.704	<0.00001 ***
R-squared =0.391 F-statistic 1.957 Durbin-Watson stat 2.0046				

Source: Author's own estimate

We note from Table 4 that the coefficients of intercept, and dummy variables for the months of February, April, July, Augst, September, October to be statistically significant. The average return in the benchmark month of January is 1.4375 percent.

Except for few months, returns are higher for all months as compared to the benchmark month of January. The relatively higher returns occur in the month of October. The returns for the months of April, June and October are positive and reasonable one as compared to the month of January.

Excepting February, April, August, September and December, returns are lower for March, May, June, July, October and November as compared to the benchmark month of January. The relatively lowest return occurs in the month of October.

The statistically significant coefficients for the intercept term, which represents the benchmark month of January, and six other months, viz., February, April, July, Augst, September, October clearly indicate the presence of seasonality in the Sensex returns. Our results confirm the January effect for stock returns in India. It is interesting to note that the Indian tax year ends in March. The average return for March is negative as compared to the January average return. As stated earlier, the coefficient of the dummy variable for the month of April is statistically significant. This evidence is consistent with the 'tax-loss-selling' hypothesis. It appears that investors in India sell shares that have declined in values, and book losses to save taxes. This causes share prices to decline which results in lower returns. As regards the year-end effect, we notice that the coefficient of dummy variables for the months of November and December are not statistically significant. The coefficients of dummy variable for the month of August and September and October are statistically significant. This could result from several social, economic and political factors (such as flood that usually comes during August –October in India in particular and Other Asian Countries in general) that may cause changes in the macroeconomic fundamentals (floods may slow down economic activities and industrial production) affecting the stock market activities.

5. Conclusion

The objective of the study is to explore the presence of seasonality in stock returns in India. For this, we have used the monthly data of the BSE's Sensex for the period from January, 1991 to December, 2010. The analysis of descriptive statistics suggests that the maximum average return occurs in the month of September and minimum average returns result in the month of October. The positive average returns arose for eight months and negative for the remaining four months. The study further documents a statistically significant coefficient for the month of for the months of February, April,July,Augst,September,October .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. The Indian tax year ends in March. The statistically significant coefficient for April is consistent with the 'tax-loss selling' hypothesis. Our results also supported the January effect. These findings have important implications for the financial managers, financial analysts and investors. The understanding of seasonality would help them to develop appropriate investment strategies.

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