IS THERE SEASONALITY IN THE SENSEX MONTHLY RETURNS?

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ABSTRACT

The presence of the seasonal or monthly effect in stock returns has been reported in several developed and emerging stock markets. This study investigates the existence of seasonality in India's stock market. It covers the post-reform period. The study uses the monthly return data of the Bombay Stock Exchange's Sensitivity Index for the period from April 1991 to March 2002 for analysis. After examining the stationarity of the return series, we specify an augmented auto-regressive moving average model to find the monthly effect in stock returns in India. The results confirm the existence of seasonality in stock returns in India and the January effect. The findings are also consistent with the 'tax-loss selling' hypothesis. The results of the study imply that the stock market in India is inefficient, and hence, investors can time their share investments to improve returns.

Key words: Market efficiency; efficient market hypothesis; tax-loss selling hypothesis; information hypothesis; stationarity; seasonality.

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Introduction

The topic of capital market efficiency is amongst the most researched areas in finance. Capital markets are considered efficient informationally. The weak form of market efficiency states that it is not possible to predict stock price and return movements using past price information. Following Fama (1965; 1970), a large number of studies were conducted to test the efficient market hypothesis (EMH). These studies generally have shown that stock prices behave randomly. More recently, however, researchers have collected evidence contrary to the EMH. They have identified systematic variations in the stock prices and returns. The significant anomalies include the small firm effect and the seasonal effect. The existence of the seasonal effect negates the weak form of the EMH and implies market inefficiency. In an inefficient market investors would be able to earn abnormal returns, that is, returns that are not commensurate with risk.

More recently, one could witness the increasing attention being accorded by the capital market analysts, portfolio managers and researchers to the emerging capital markets (ECMs) due to the growing internationalisation of the world economy and globalisation of the capital markets. There are a few studies that have examined the issue of seasonality of stock returns in the ECMs. The objective of this study is to investigate the existence of seasonality in stock returns in India. We use monthly closing share price data of the Bombay Stock Exchange's Sensitivity Index (Sensex) from April 1992 to March 2002 for this purpose. The Indian tax system differs from the USA and many other developed and developing countries. The tax year ends in March in India and not in December like in the USA. The taxpayers have to pay capital gain tax on the sale of shares. The capital losses can be set off against the capital gains. Both the resident and non-resident investors are liable to pay taxes. The 'tax-loss-selling' hypothesis may provide an explanation for the seasonality in stock returns in India. Yet an alternative explanation may be provided by the information hypothesis (Kiem, 1983).

This study specified an autoregressive moving average model with dummy variables for months to test the existence of seasonality in stock returns. The results of the study confirmed the monthly effect in stock returns in India and also supported the 'tax-loss selling' hypothesis. These findings have important implications for financial managers, financial analysts and investors. The understanding of seasonality should help them to develop appropriate investment strategies.

Review of Prior Research

There would exit seasonality 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. In the USA and some other countries, the year-end month (December) is the tax month. Based on this fact, a number of empirical studies have found the 'year-end' effect and the 'January effect' in stock returns consistent with the 'tax-loss selling' hypothesis. It is argued that investors, towards the end of the year, sell shares whose values have declined to book losses in order to reduce their taxes. This lowers stock returns by putting a downward pressure on the stock 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, that is, in the month of January.

In the US market, a number of studies have found the seasonal or the year-end effect in stock. Wachtel (1942) was the first to point out the seasonal effect in the US markets. Rozeff and Kinney (1976) found that stock returns in January were statistically larger than in other months. Keim (1983) investigated the seasonal and size effects in stock returns. He showed that small firm returns were significantly higher than large firm returns during the month of January. He attributed this effect to the 'tax-loss-selling' hypothesis and the 'information' hypothesis. Reinganum (1983) arrived at similar conclusions, but he found that the tax-loss-selling hypothesis could not explain the entire seasonality effect. There is also evidence of the day-of-the-week effect in the US (Smirlock and Starks, 1986) and other markets (Jaffe and Westerfield, 1985; 1989) and intra-month effects in the US stock returns (Ariel, 1987).

The issue of the seasonality of stock returns has been investigated in many other developed countries. The existence of seasonal effect has been found in Australia (Officer, 1975; Brown, Keim, Kleidon and Marsh, 1983), the UK (Lewis, 1989), Canada (Berges, 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. In a study of 17 industrial countries with different tax laws, Gultekin and Gultekin (1983) confirmed the January effect. Jaffe and Westerfield (1989) found a weak monthly effect in stock returns of many countries.

The research on the seasonal effect in the ECMs has started surfacing recently. A few studies have revealed the presence of seasonal effect of stock returns for the ECMs (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). Ramcharran (1997), however, rejected the seasonal effect for the stock market in Jamaica. In this study, we extend the investigation of the monthly effect in stock returns for the Indian stock market.

Methodology and Data

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 criticised 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 easily detectable in the market indices or large portfolios of shares rather than in individual shares (Officer, 1975; Boudreaux, 1995). This study analyses returns of the BSE's Sensitivity Index. We measure stock return as the continuously compounded monthly percentage change in the share price index as shown below:

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

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

The results of the OLS regressions will be spurious if the dependent variable is non-stationary. We first determine whether the Sensex 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). We also use a formal test of stationarity, that is, the Augmented Dickey-Fuller (ADF) test. The ADF test is a common method for determining unit roots. It consists of regressing the first difference of the series against a constant, the series lagged one period, the differenced series at n lag lengths and a time trend (Pindyck and Rubinfeld, 1998, p. 509):

$$\Delta r_t = \alpha + \sum_{i=1}^{n} \beta_i \Delta r_{t-i} + \lambda t + \rho r_{t-1} + \varepsilon_t \tag{2}$$

If the coefficient of ρ is significantly different from zero, then the hypothesis that *r* is non-stationary is rejected. The ADF test can be carried out with and without the constant and/or trend. One has also to choose the appropriate lag length. If a series is found to be non-stationary in level, one should difference the series until the stationarity is established.

We will next conduct a test for 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. Thus, similar to earlier studies, our initial model to test the monthly seasonality is as follows:

$$\begin{aligned} y_t = {} & \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} \\ & + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t \end{aligned} \tag{3}$$

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 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. The problem with this approach is that the residuals may have serial correlation.

We improve upon Equation (3) by constructing an ARIMA model for the residual series μ_t. We then substitute the ARIMA model for the implicit error term in Equation (3). The augmented model is as follows:

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

where η_t is a normally distributed error term and it may have different variance from ε_t (Pindyck and Rubinfeld, 1998, p.590). We also check for the ARCH effect in residuals. As we show later, since we not find any ARCH effect, we do not make any adjustment in the 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 April 1991 to March 2002. This constitutes a sample size of 132 monthly observations. The Indian economy and capital market witnessed significant economic reforms and deregulation after 1991. Therefore, our study covers post-reform period.

Results

We first present descriptive statistics for the entire period and each month in Table 1. There are wide variations of returns across months. Returns for the months of January, February, August and December are higher than returns of other months. The maximum average return occurs in the month of February. Returns in the months of March, April, May, September, October and

November are negative. Stock returns show negative skewness for six months and positive for other six months. They also show leptokurtic (kurtosis >3) distribution for four months. That means flatter tails than the normal distribution. The Jarque-Bera test indicates that returns are normally distributed in all months. Given positive skewness and excess kurtosis for many months, this result is suspicious. It may possibly be due to small sample size for each month. The average monthly return (0.356 percent) for the entire period from April 1991 to March 2002 is positive. The return series for the entire period show high dispersion, and it is leptokurtic and skewness is positive. The Jarque-Bera test shows that returns are not normally distributed.

Table 1: Descriptive Statistics, the Sensex Returns: April 1991-March 2002

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**1991-02**
Mean	1.718	2.915	-0.686	-0.332	-0.212	0.514	0.459	1.170	-0.581	-1.728	-0.150	1.208	0.358
Median	1.700	3.060	-2.090	-1.040	0.950	1.010	0.500	1.960	0.290	-1.030	-0.030	1.490	0.300
Maximum	8.140	11.750	15.230	5.800	7.620	5.440	10.910	5.360	3.610	2.660	8.250	3.630	15.23
Minimum	-5.490	-2.430	-7.130	-5.100	-11.170	-5.460	-5.290	-4.570	-6.230	-6.550	-5.820	-2.130	-11.17
Std. Dev.	4.350	3.906	6.404	3.718	4.709	2.960	4.509	3.462	3.193	2.563	4.293	1.758	3.999
Skewness	-0.123	0.862	1.424	0.504	-0.827	-0.382	0.935	-0.429	-0.377	-0.303	0.444	-0.295	0.440
Kurtosis	2.103	3.496	4.482	2.046	4.136	2.871	3.729	1.837	1.846	2.586	2.385	2.337	4.203
Jarque-Bera	0.397	1.474	4.723	0.882	1.846	0.275	1.847	0.957	0.871	0.247	0.535	0.361	12.22
Probability	0.820	0.479	0.094	0.643	0.397	0.871	0.397	0.620	0.647	0.884	0.765	0.835	0.002
Obs.	11	11	11	11	11	11	11	11	11	11	11	11	132

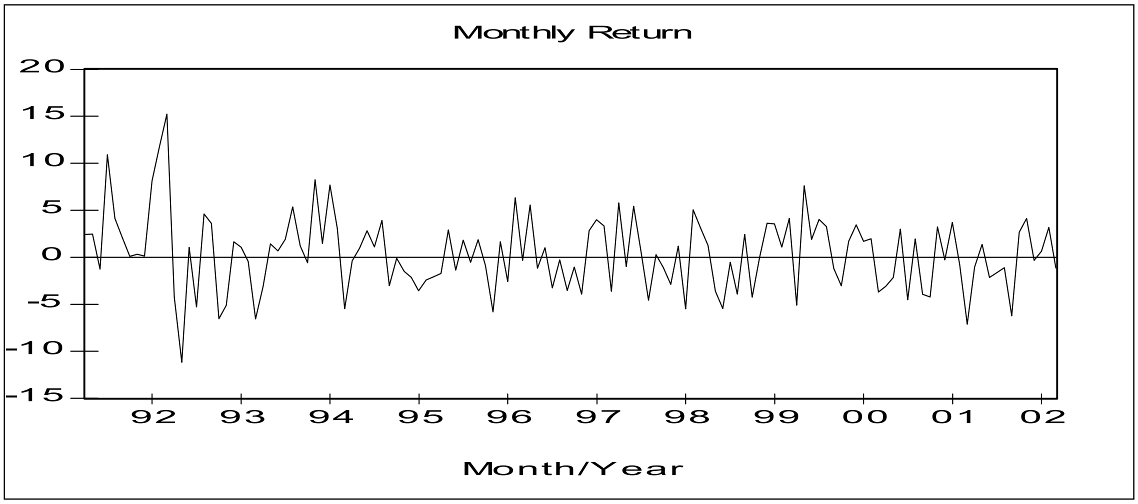

Figure 1: Monthly Sensex Returns, April 1991-March 2002

Figure 1 gives the plot of the return series, which shows variations in monthly returns. In Figures 2 and 3 we 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 in Figure 3 also does not indicate any large spikes. In Table 2 we present result of the ADF tests. Each of the test scores is well below the critical value at 5 percent level. 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.

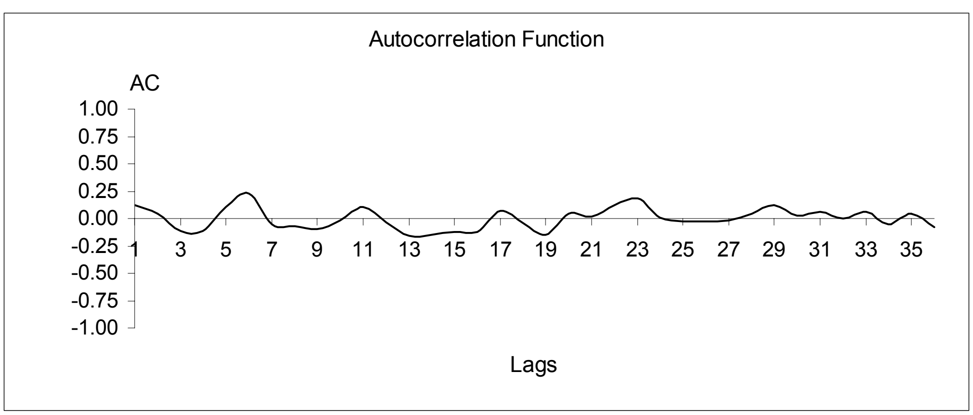

Figure 2: Autocorrelation Function of the Sensex Returns

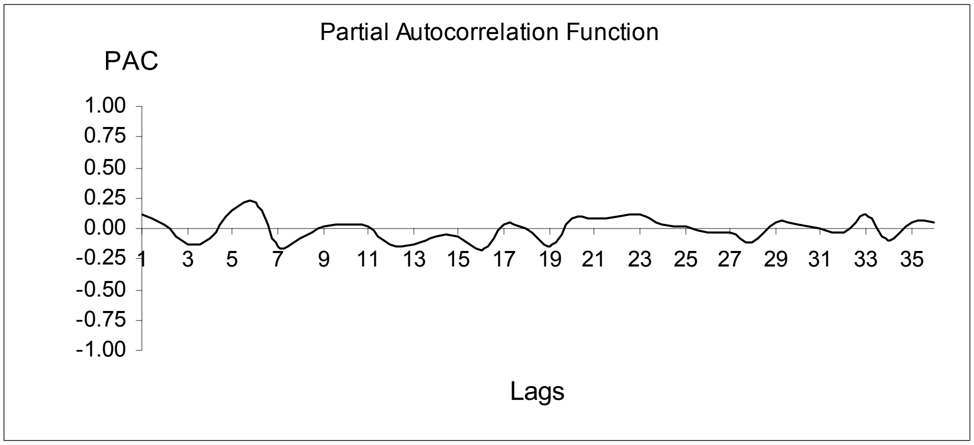

Figure 3: Partial Autocorrelation Function of the Sensex Returns

Table2: Augmented Dickey-Fuller Stationarity (ADF) Test

ADF: with constant		**ADF: with constant & trend**	
5 lags	-3.6953	5 lags	-3.6804
	(-2.8844)		(-3.4458)
10 lags	-3.9906	10 lags	-3.8463
	(-2.8853)		(-3.4472)

Parentheses have critical t-statistics for ADF stationarity testing. A value greater than the critical t-value indicates non-stationarity.

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. None of the coefficients is significant. R^2 of 0.09 is low, and the insignificant F-statistic suggests poor model fit. Durbin-Watson statistic of less than 2 indicates serial correlation in the residuals. Further, the Ljung-Box Q-statistic for the hypothesis that there is no serial correlation up to order of 24 is 37.11 with a significant ρ-value of 0.043 is rejected. The Ljung-Box Q-statistic to order of 36 is 47.90 and it is also significant at 0.089. Thus, the residuals of the model are not white noise.

Table 3:The Regression Model to Test Seasonality

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	1.718	1.202	1.430	0.16
D2 (Feb)	1.196	1.699	0.704	0.48
D3 (Mar)	-2.405	1.699	-1.415	0.16
D4 (Apr)	-2.050	1.699	-1.206	0.23
D5 (May)	-1.930	1.699	-1.136	0.26
D6 (Jun)	-1.205	1.699	-0.709	0.48
D7 (Jul)	-1.259	1.699	-0.741	0.46
D8 (Aug)	-0.548	1.699	-0.323	0.75
D9 (Sep)	-2.299	1.699	-1.353	0.18
D10 (Oct)	-3.446	1.699	-2.028	0.04
D11 (Nov)	-1.868	1.699	-1.099	0.27
D12 (Dec)	-0.510	1.699	-0.300	0.76
R^2	0.090	F-stat	1.082	
D-W stat.	1.79	Prob.	0.381	

We next examine the residuals obtained from the estimation of Equation (3). Figures 4 and 5 show the sample autocorrelation and partial autocorrelation functions for the residuals. The steadily declining autocorrelation function implies that the residuals series is stationary. After experimenting, we fit the ARIMA (6,0,2) model to the residual series. The results of the model are given in Table 5. The Ljung-Box Q-statistic to order of 36 is 34.42 is insignificant with ρ-value of 0.188. Thus, we can conclude that the residuals of the ARIMA model are white noise.

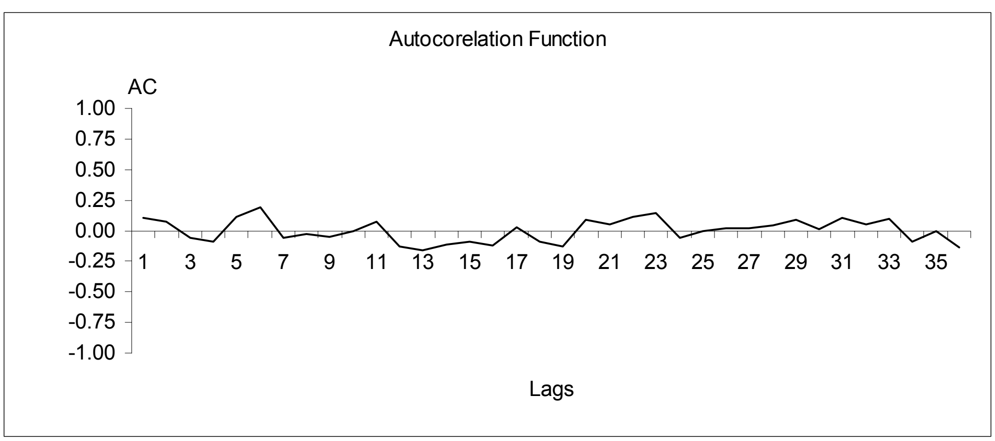

Figure 4: Autocorrelation Function of the Residual Series

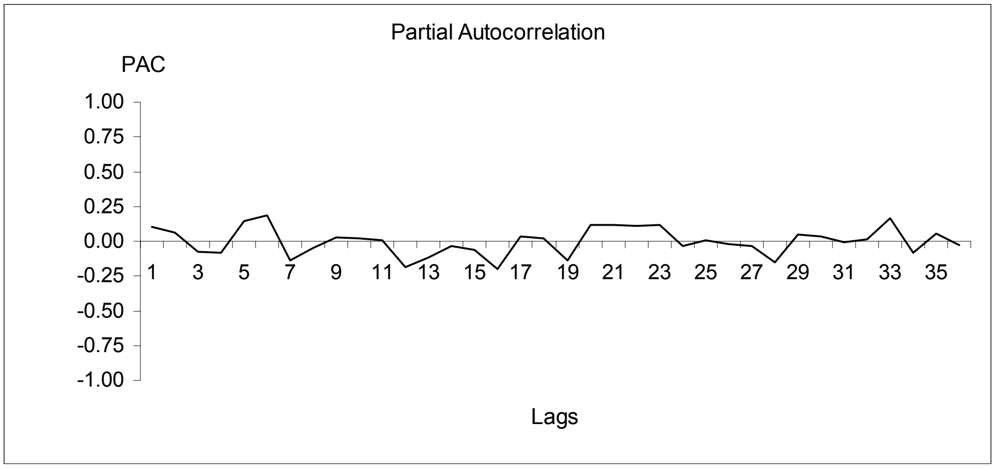

Figure 5: Partial Autocorrelation Function

Table 4: ARIMA Model for the Residuals of Equation (3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.195	0.351	-0.556	0.58
AR (1)	-0.066	0.091	-0.728	0.47
AR (2)	-0.698	0.090	-7.748	0.00
AR (3)	-0.019	0.108	-0.172	0.86
AR (4)	-0.094	0.108	-0.866	0.39
AR (5)	-0.047	0.085	-0.556	0.58
AR (6)	0.073	0.084	0.871	0.39
MA (1)	0.166	0.003	50.48	0.00
MA (2)	0.980	0.000	2113.8	0.00
R^2	0.228	F-stat	4.325	
D-W stat	1.99	Prob	0.00	

We combine the ARIMA model with the regression model (Equation 3) and estimate all parameters simultaneously as given in Equation (4). The results of the estimation of Equation (4) are given in Table 5. The R^2 is 0.32 and the D-W statistic is very close to 2. The sample autocorrelations for the residuals of the model [Equation (5)] are almost zero. Further, the Ljung-Box Q-statistic is mostly insignificant. Thus, the residuals of the model are white noise. Hence, our estimations do not suffer from the problem of serial correlation. The residuals do not exhibit conditional autoregressive heteroskedasticity. A Lagrange Multiplier (LM) test for the presence of the ARCH effects in the residuals (F-statistic of 0.279 and ρ-value of 0.60) reveals no such effects.

We note from Table 5 that the estimated coefficients of the monthly dummy variables change significantly once we account for the serial correlation in the residuals. We find the coefficients of intercept, and dummy variables for the months of March, July and October to be statistically significant. The average return in the benchmark month of January is 1.85 percent. Except for the month of February, returns are lower for all months as compared to the benchmark month of January. The relatively lowest return occurs in the month of October. The returns for the months of March, July and October are amongst the lowest as compared to the month of January.

Table 5: The Time Series and Regression Model [Equation (5)]

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	1.835	0.966	1.900	0.06
D2 (Feb)	0.949	1.511	0.628	0.53
D3 (Mar)	-2.569	1.447	-1.776	0.08
D4 (Apr)	-1.994	1.618	-1.233	0.22
D5 (May)	-2.225	1.591	-1.398	0.16
D6 (Jun)	-1.419	1.490	-0.953	0.34
D7 (Jul)	-2.496	1.321	-1.890	0.06
D8 (Aug)	-0.877	1.498	-0.586	0.56
D9 (Sep)	-2.629	1.635	-1.608	0.11
D10 (Oct)	-4.144	1.546	-2.680	0.01
D11 (Nov)	-2.209	1.461	-1.512	0.13
D12 (Dec)	-0.218	1.476	-0.148	0.88
AR (1)	0.000	0.099	0.003	1.00
AR (2)	-0.682	0.095	-7.211	0.00
AR (3)	-0.046	0.113	-0.406	0.69
AR (4)	-0.079	0.114	-0.696	0.49
AR (5)	-0.002	0.091	-0.021	0.98
AR (6)	0.100	0.089	1.123	0.26
MA (1)	0.085	0.042	2.026	0.05
MA (2)	0.980	0.000	2845.6	0.00
R^2	0.324	F-stat	2.676	
D-W stat	1.98	Prob.	0.00	

The statistically significant coefficients for the intercept term, which represents the benchmark month of January, and three other months, viz., March, July and October clearly indicate the presence of seasonality in the Sensex returns. Our results do confirm the January effect for stock returns in India. It is interesting to note that the Indian tax year ends in March in contrast with the US tax system where the tax year ends in December. 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 March 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 that results in lower returns. As regards the year-end effect, we notice that the coefficients of dummy variables for the months of November and December are not statistically significant. However, we do find the coefficients of dummy variable for the month of October and the intercept, representing January to be statistically significant. This could result from several social, economic and political factors. These results of the study could be attributed to the 'information' hypothesis.

Summary and Conclusions

The focus of this study was on investigating the existence of seasonality in stock returns in India. We used the monthly returns data of the BSE's Sensex for the period from April 1991 to March 2002. The analysis of descriptive statistics showed that the maximum average return (positive) occurred in the month of February and lowest (negative) in the month of March. The positive average returns arose for six months and negative for the remaining six months. The regression results confirmed the seasonal effect in stock returns in India. We found that returns were statistically significant in March, July and October. The Indian tax year ends in March. The statistically significant coefficient for March is consistent with the 'tax-loss selling' hypothesis. Our results also supported the January effect.

The results of the study indicate that stock returns in India are not entirely random. This implies that the Indian stock market may not informationally efficient. As a consequence, perhaps investors can improve their returns by timing their investments. We would, however, like to caution that more research is needed before making any firm conclusion in this regard. In the future, one could study other stock indices (like the BSE's National Index, the NSE's Nifty etc.) in India and also investigate the weekly and the intra-month effects.

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