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EFFICIENT MARKET HYPOTHESIS AND CALENDAR EFFECTS: EMPIRICAL EVIDENCES FROM THE INDIAN STOCK MARKETS

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ABSTRACT

The Efficient Market hypothesis is a cornerstone of modern investment theory that essentially advocates the futility of information in generation of abnormal returns in capital markets over a period of time. However, the existence of anomalies challenge the notion of efficiency in stock markets. Calendar effects, in particular, violate the weak form of efficiency, highlighting the role of past patterns and seasonality in estimating future prices. The present research aims to study the efficiency in Indian stock markets. Using daily and monthly returns of NIFTY 50 data from its inception in January 1995 to December 2015, we employ dummy variable multiple linear regression technique to assess the existence of calendar effects in India stock markets. To correct for volatility clustering and ARCH effect present in the daily returns, the results are modelled using the EGARCH estimation methodology. The study reveals the existence of calendar effects in India in form of a significant Wednesday Effect as well as a significant 'December effect', thereby suggesting that the Indian stock markets do not show informational efficiency even in the weak form, a trait observable in emerging markets.

KEYWORDS: Calendar effects, EMH, Dummy Variable Regression, Day-of-the-week effect, Month-of-the-year effect, NIFTY

INTRODUCTION

Market efficiency enunciates that since all relevant information is reflected in the stock prices, it is impossible to outperform the market consistently. It subscribes to the notion that the price changes are unpredictable and dependent on information, which arrives randomly. Bachelier (1900), in his thesis 'Theory of Speculation', first introduced the idea of random and unpredictable price changes, which Fama (1965) later evolved into the concept of market efficiency. The market efficiency hypothesis has emerged in recent decades due to works of Malkiel (1973), Beja (1977), Grossman and Stiglitz (1980), Lo and MacKinlay (1988), Lehmann (1990) etc. and due to its theoretical underpinnings, is still of immense interest in research. In

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words of Fama (1970), "*A market in which prices always fully reflect available information is called efficient*." He further stated the sufficient conditions for market efficiency as:

I. No transaction costs in trading securities;
II. Costless and accessible information to all market participants;
III. Complete consensus between the market participants on the implications of available information on the stock prices and the future distribution of stock prices.

In an informationally efficient market fulfilling the sufficient conditions, prices fully reflect all the available information. However, in the actual observed world, it is difficult to find a market exhibiting all the above mentioned conditions simultaneously. However, Fama (1970) maintains that while these conditions are sufficient, they are not necessary. The violation of one or more of these conditions does not necessarily lead to market inefficiency. The effect of the distortions created when these sufficient conditions are violated are of substantial interest to researchers of market efficiency. As elaborated by Roberts (1967) and further, Fama (1970), market efficiency is categorised into three forms based on the type and absorption of the information reflected in the stock prices. These can be classified into weak, semi-strong and strong forms of market efficiency. Weak form of efficiency implies all past information in the markets is completely reflected in the stock prices and analysis of past information is irrelevant in prediction of future price movements. Semi-strong form of market efficiency states that stock prices reflect all information available publicly. It enlarges the scope of prices to include both past information and currently prevalent information i.e. it relates to the idea that the stock prices instantaneously adjust to the news arriving in the market in addition to the past information. Strong form of market efficiency is the broadest form comprising of both the weak and semi-strong forms. It implies that all information, whether public or private information, is reflected in the stock prices.

At some point in time, markets can exhibit some degree of inefficiency. Such inefficiencies are majorly caused by anomalies which induce a predictable pattern of price and volume movements in the market. Such anomalies affecting market inefficiency have been classified in research as fundamental, technical and calendar anomalies. Fundamental anomalies pertain to semi-strong form of market efficiency. The objective of fundamental analysis is to search and evaluate stocks that systematically outperform other category stocks in the market. Basically, fundamental anomalies relate to anomalies in the valuation of stock prices. One example of the fundamental anomalies can be seen in valuations based on the book-to-market ratio. Research in 1990s (Mark et al, 1993) indicates that within a certain period companies with low ratios outperform the companies with high book to market ratio. This pertains to the fact that stock prices of well-known companies are overestimated, whereas stock prices of lesser known companies are underestimated. On the other hand, technical and calendar anomalies relate to the weak form of market efficiency. Technical anomalies create predictability in movements of stock price which can be exploited through technical analysis of historical information of price and volume to earn abnormal returns on stocks. These anomalies make it possible to predict future price changes by analyzing past information. A common example is a technical analysis technique using moving average or momentum strategy with the latter suggesting application of a contrarian strategy to earn above normal returns. When such an anomaly exists in the market, technical analysis helps in generation of a trading rule to outperform the market. Calendar anomalies arise due to seasonality in the stock, i.e. the stock price is systematically lower or higher in a particular calendar period. These anomalies can be seen as the distribution of stock returns being unequal for certain periods of time. For example, the Weekend effect is a calendar anomaly such that the returns on an index are systematically higher on Friday and lower on Monday. Calendar effects imply that at a particular day, month or period of the year stock returns behave contrary to the market efficiency hypothesis. This anomaly is reflected in the varying distribution of stock returns within the period of study with such variation presenting a systematic pattern. Hence, the existence of calendar effects can entail emergence of predictable patterns in returns exploitable by investors to earn above normal returns. Some calendar effects can be described as:

- *Day-of-the-week effect:* The day-of-the-week effect relates to the significant inequality in mean of returns for different days of the week.
- *Month-of-the-year effect:* This calendar effect relates to the significant inequalities in the mean of returns for different months of the year, i.e. a particular month generates a significantly different (higher or lower) return than the other remaining months in the year.
- *Weekend effect:* The observation that mean returns on Monday are the smallest and sometimes even negative, while mean returns on Friday are positive and highest compared to returns on other days of the week is known as the weekend effect.
- *Turn-of-the-month and intra-month effects:* A turn-of-the-month effect is found where the stock prices rise on the last trading day in the month and the first few trading days of the following month. The intra-month effect is seen in patterns of returns where there are significantly unequal distribution of returns within a month i.e. high positive returns in the first half of the month as compared to the succeeding second half.
- *Turn-of-the-year effect/ January effect:* The turn-of-the-year effect pertains to the seasonal pattern in the stock markets associated with increasing trading volumes and comparatively higher stock prices in the last week of December and the first two weeks of January.

The Efficient Market Hypothesis has important implications for investors and firms alike. In an efficient market, information is instantly reflected in the stock prices, so obtaining released and available information will not help an investor to outperform the market. Furthermore, since reflected information makes the price of the stock to be fair and representative, firms cannot profit from deluding investors in the market. However, anomalies relate to a kind of distortion that contradicts the efficient market hypothesis. Specifically, the presence of calendar anomalies in stock returns violate the weak form of market efficiency as equity prices do not remain random and their future values can be predicted on observed past patterns. Market participants such as day traders can devise trading strategies which could fetch abnormal profits based on the deduced past pattern. For example, if the past stock returns show evidences of 'weekend effect', investors could execute a trading strategy of selling securities on Fridays and buying on Mondays to make excess profits. Thereby, the presence of market anomalies, such as calendar effects, provides results deviating from the EMH and creates opportunity to earn abnormal returns through the existing information.

REVIEW OF LITERATURE

The review of literature reveals a distinctive regionality in the level of efficiency in the stock markets around the word. In practice, the efficiency of markets varies through different markets and countries. Studies on American, European and Asian markets reveal the differences in the calendar effects observed in these markets. Calendar effects themselves were first reported as a form of seasonality by Watchel (1942) for the first time. Rozeff and Kinney (1976) found the January effect in New York Exchange stocks for the period 1904 to 1974 as the mean return for the month of January was higher than the mean returns of other months. A similar conclusion was drawn by Reinganum (1983) who opined that the entire seasonality in stock returns could not be explained by the tax-loss-selling hypothesis alone. Gultekin and Gultekin (1983) studied the stock markets of sixteen industrial countries and provided evidence to support calendar effects in the stock market in form of January returns, which was found to be exceptionally large in fifteen of sixteen countries under study. Similarly, Brown et al. (1985) studied the monthly returns of Australian stock market and found the prevalence in December-January and July-August effects. They attribute this to the financial year in Australia being from June to July. Mill and Coutts (1995) reported similar calendar effects in FTSE 100, Mid 250 and 350 indices for the period 1986 and 1992. A January effect was reported by Choudhary (2001) in the UK and US returns but similar evidence could not be found in case of German returns. However, Borges (2009) critiqued the earlier methodologies of analysing and modelling stock returns and proposed a new methodology of single variable dummy regression analysis to examine day-of-the-week and month-of-the-year effects in seventeen European stock market indices in the period 1994-2007. They use GARCH and bootstrapping techniques in addition to standard OLS procedures to find significant calendar effects in form of August and September effects in country specific returns. However, recent studies by Yavrumyan (2015) suggest that there are no calendar anomalies in returns of the Oslo stock indices in the post global financial crisis period, thereby providing support towards market efficiency.

In the Indian context, early studies by Sharma and Kennedy (1977), Choudhury (1991) and Obaidulla (1994) could not provide any substantial proof of calendar effects or informational inefficiency. It was Broca (1992) who first presented strong evidence of the existence of day-of-the-week effect by studying that the BSE NATEX daily returns to conclude that Wednesdays had the lowest mean returns. Further, using the SENSEX monthly returns data from April 1991 to March 2002, Pandey (2002) confirms the existence of anomalies in stock markets in India during the post-reform era and attributes it to the 'tax-loss selling' hypothesis. Using a non parametric Kruskall-Wallis Test, Sarma (2004) tested daily returns of three indices SENSEX, NATEX, and BSE200 for the period January 1st 1996 to August 10th 2002 for the presence of seasonality and found that the Monday-Friday set for all the indices had the highest positive deviation, thereby indicating the opportunity to make abnormal returns through a strategy of buying on Mondays and selling on Fridays. Sah (2008) further tested the calendar effects in both daily and monthly NIFTY and NIFTY junior indices using GARCH modelling and found the existence of both day-of-the-week and month-of-the-year effects in NIFTY as well as NIFTY junior over the study period of January 2005 to December 2008. Patel (2008) also studied the calendar effects in monthly mean returns in Indian stock markets to find two distinct effects; a November-December effect, where the mean returns for both November and December were significantly higher than other months, and a March-to-May effect, where mean monthly returns from March to May were significantly lower than the remaining nine months. It was also seen that these effects existed independently of each other. Extending the study to four Asian markets of India, China, Japan and Hong Kong, Patel & Radadia (2012) analysed the daily returns of the stock exchanges of these four countries and found a significant Monday effect in these countries. Recently, Purohit & Tyagi (2015) compared the patterns of monthly return in India and China and found both countries to exhibit a month-of-the-year pattern. Specifically, using a eighteen year period from 1995 to 2013, they found 'December effect' to exist in India whereas China exhibited a 'May-effect'. They attribute these effect to pre-budgetary expectations in case of China and increased economic activity due to festivals for India. However the literature review reveals certain aspects about the existing body of research on the existence of calender effects in India.. First, the existing body of literature has used either a limited time window for selection of their data picked randomly between selective dates withour prior justification. Second, most research suffer from model misspecification in terms of the effects of volatilty clustering. As such, it is pertinent to update the existing body of research while employing the necessary time series analysis techniques to get the most representative results.

RESEARCH METHODOLOGY

The study focuses on the broad daily and monthly return patterns in the Indian stock markets. To derive significant results, the NIFTY 50 has been taken as the benchmark index representing the Indian stock markets. The NIFTY 50 is a diversified stock index covering fifty companies accounting for thirteen sectors of the economy and is owned and managed by India Index Services and Products Ltd (IISL). It follows a free float market capitalization weighted method, where the level of the index shows the total market value of all the stocks in the index relative to a particular base period, in this case the base period being November 3, 1995. For studying the day-of-the-week effect, the daily data of the closing index values ranging from January 1st, 1996 to December 31, 2015 comprising of 5222 observations were obtained from the NSE website. This data has been classified according to day-of-the-week -Monday through Friday- for testing the equality of mean returns of the day. To study the month-of-the-year-effect, the closing values of the index on the last trading day were taken to accumulate 252 observations over the same date range. Similarly, the data has been classified on a monthly basis for testing the equality of the mean returns of the month. The period of study extensively covers a twenty one year period of the NIFTY 50 since its inception to obtain results of greater confidence.

For the purpose of the study, the returns are computed as:

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

Where r_t *is* the log return of the stock market index and P_t is the stock index at date *t.* The log returns are continuous rates of returns, computed as the log of the ratio of the current time period's price (daily or monthly) to the previous time period. The log returns are preferred over linear returns primary due to ease of calculation, since they are given by the first order difference of the logarithmic prices.

Since the study employs time series data analysis technique, the regression results may be spurious if the data series if non-stationary. The stationarity of the data can be checked using Unit-root test. The existence of a unit root indicates that the data is non-stationary. Further, as documented by Connolly (1989, 1991), several specific problems arise when using approach the standard OLS estimation procedures in time series analysis that do not account the time-dependent changes in volatility in financial market returns. These include (i) autocorrelation of the stock market index returns (ii) non-normality of the residuals (iii) and the variance of the residuals may not be constant. As such, it is important to check for heteroskedasticity in the residuals to account for time varying volatility normally seen in stock return series. Accordingly, the ARCH LM test is employed and the results are interpreted at 5% level of significance with the null hypothesis that no ARCH effect exists in the log return series.
Model Specification.

The study of seasonality with respect to daily and monthly patterns in the stock returns of NIFTY 50 employs Dummy Variable Regression model. The technique quantifies qualitative aspects, such as months, as explanatory variables in the regression model. A dummy variable (are also called categorical, indicator or binary variable) is a variable which takes only two values of 1 or 0. While 1 indicates the presence of an attribute, 0 indicates the absence of the attribute. In general, for categorical variables with q categories, (q-1) dummies are needed, with one category being omitted. The estimated intercept for the equation will represent the intercept for the omitted category and the coefficients will represent the intercepts for other categories.

To examine the days of the week effect, the following dummy variable regression model is specified as follows:

Nifty returns = $\beta_0 + \beta_1 Tuesday + \beta_2 Wednesday + \beta_3 Thursday + \beta_4 Friday + \mu$ ....(1)

For studying the month-of-the-year effect in the series, the model is specified as

Nifty returns = $\beta_0 + \beta_1(d_{Feb}) + \beta_2(d_{Mar}) + \beta_3(d_{Apr}) + \beta_4(d_{May}) + \beta_5(d_{Jun}) + \beta_6(d_{July}) + \beta_7(d_{Aug}) + \beta_8(d_{Sept}) + \beta_9(d_{Oct}) + \beta_{10}(d_{Nov}) + \beta_{11}(d_{Dec}) + \mu$ ....(2)

HYPOTHESIS

For testing the days-of-the-week effect, our hypothesis is that returns across all days are equal i.e.

$H_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4$

H_1: Atleast one β is different

Similarly, for testing the month-of-the-year effect, the hypothesis is framed as

$H_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11}$

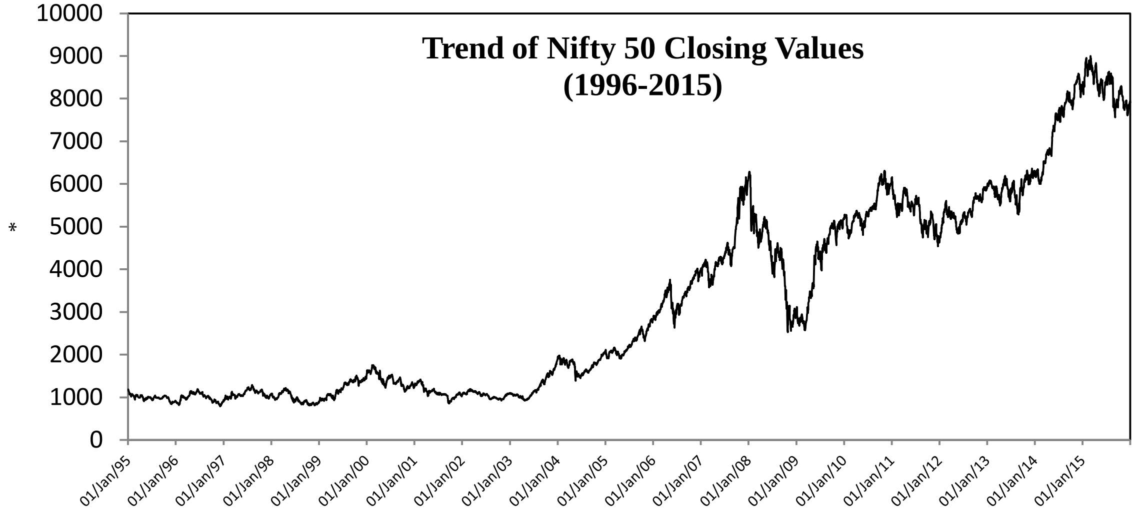
H_1: Atleast one β is different

If the dummy variable for any particular day/month is significant, we know that particular day/month to have a significant return effect. If no seasonal pattern exists, the hypothesis that the coefficients are all zero should not be rejected. However, in presence of ARCH effect, the dummies found significant in the results obtained from the standard OLS estimation are used as explanatory variables for the ARCH family models. These 'significant dummies' from the OLS regression will be truly anomalous only if they remain significant in the mean equation of the ARCH family regression models. Else, it can be concluded that the excess return is due to varying market volatility.

RESULTS AND DISCUSSION

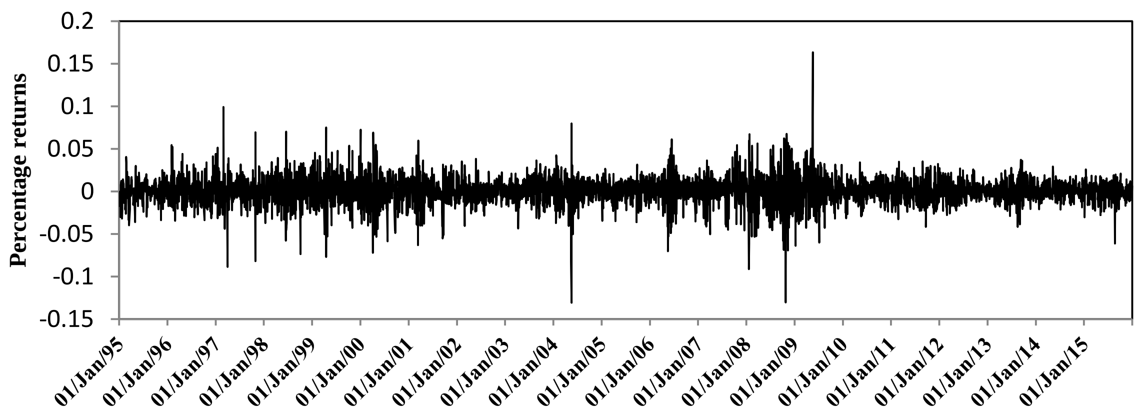
Before analyzing descriptive statistics for the log returns on the NIFTY 50 index, it is relevant to observe time series plots for the closing index values and log returns series.

Graph 1: NIFTY 50 closing values

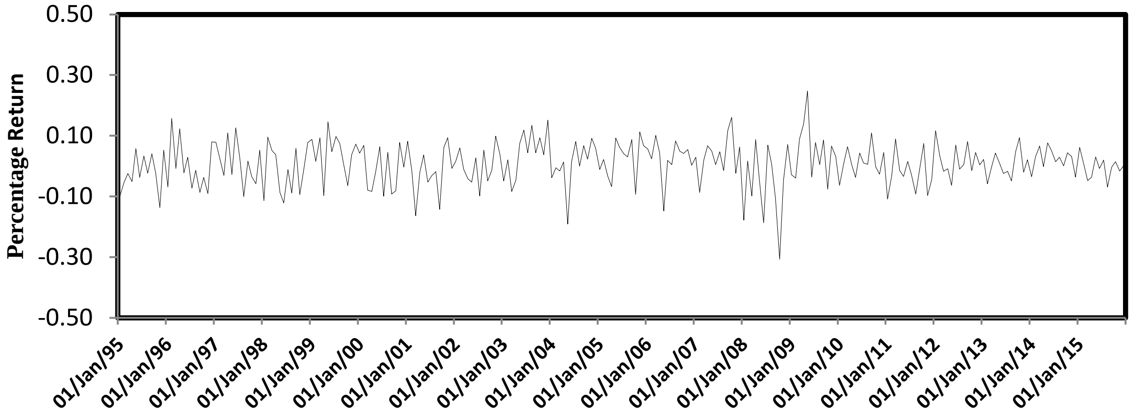


Graph 1 presents series on the closing values of the NIFTY 50 index. It is visible that at certain points in time, prices on the index move slowly, whereas at other time points, the movement is faster. This is because of the news and information announced within that particular time period with positive news conducing prices to grow and negative information causing them to decline. From this graph, the price growth before the global financial crisis in 2008 and drop in the closing prices during the crisis (2008-2009) is eminently visible.

Graph 2: Nifty daily returns for period 1996-2015



Graph 3: Monthly returns of nifty index for 1996-2015



Graph 2 and 3 presents time series for logarithmic returns on the NIFTY 50 index that emphasize period of high volatility during 2008 in both daily and monthly series, attributable to the global financial crises during the said period. From these graphs, it seems that the disturbances follow a mean reverting process and are heteroskedastic with non-constant variance. Further, periods of high and low volatility, when returns are more or less dispersed respectively, could indicate presence of volatility clustering in series. As such, these are tested through formal statistical procedures.

Next, the descriptive statistics of returns of Nifty 50 are computed as shown by Table 1.

Table 1: Descriptive Statistics of the NIFTY 50 Index

Mean	0.000365
Median	0.000741
Maximum	0.163343
Minimum	-0.130539
Std. Dev.	0.01571
Skewness	-0.15994
Kurtosis	9.871274
Jarque-Bera	10293.36
Probability (P-Value)	0.0000

As seen, the index shows a positive mean return over the study period. The skewness and kurtosis of the empirical distribution for the NIFTY 50 index deviate from the theoretical normal distribution parameters where skewness equals 0 and kurtosis equals to 3. Skewness indicates the asymmetry of the returns distribution around its mean. Kurtosis is a measure of the peakedness of the distribution. Here, the negative skewness indicates that the distribution is skewed to the left i.e it is more overspread towards negative values. In terms of data pertaining to financial returns, it highlights the significant probability of small gains and a small probability of large losses in terms of obtaining large negative returns. A kurtosis greater than 3 shows positive excess kurtosis signifying that the distribution is peaked and is fat-tailed relative to the normal distribution i.e. leptokurtic in nature. The non-normality of the data is confirmed in the results of the Jarque-Bera normality test which are significant at 5% level and allows us to reject the null hypothesis of normality of returns.

To test for stationarity of the underlying data, the Augmented Dickey Fuller Test and Phillip-Perron Test are employed with the null hypothesis that the underlying data is not stationary i.e. there is an existence of unit root. The results of ADF and PP test at level are examined in Table 2.

Table 2: Results of the Unit Root Test

Test		**Intercept** t-Statistic (p-Value)	**Trend & Intercept** t-Statistic (p-Value)	**None** t-Statistic (p-Value)
Augmented Dickey-Fuller test statistic		-67.2493 (0.0001)	-67.2694 (0.0001)	-67.24202 (0.0001)
Test critical values:	1% level	-3.43122	-3.9597	-2.56541
	5% level	-2.86186	-3.410	-1.94089
	10% level	-2.56176	-3.217	-1.61666
Phillips-Perron test statistic		-67.1584 (0.0001)	-67.1567 (0.0001)	-67.15095 (0.0001)
Test critical values:	1% level	-3.431422	-3.959796	-2.565405
	5% level	-2.861899	-3.410665	-1.940885
	10% level	-2.567003	-3.127115	-1.616659

The t-statistics and the respective p-values of both the test in the tables allow the rejection of the null hypothesis, indicating the stationarity in the returns.

Now, the model (1) is estimated to study days of the week effect in NIFTY 50 returns. The results are reported in Table 3. The benchmark day is Monday shown by the intercept which provided a return of -0.06 percent on an average during the sample period.

Table 3: Results of OLS estimation procedures for NIFTY 50 daily returns

	Coefficients	**Standard Error**	**t Stat**	**P-value**
Monday	-0.0006	0.000478258	-1.17394	0.24047115
Tuesday	0.0000	0.000681035	-0.05413	0.956833134
Wednesday	0.0031	0.000682198	4.609813	0.0000041*

Thursday	0.0007	0.000681366	1.055881	0.291071285
Friday	0.0008	0.00068508	1.230287	0.218645119
R-squared	0.005473			
F-statistic	7.176165			
Prob(F-statistic)	0.000009			

An examination of the p-values of the respective days highlights that for the NIFTY 50 returns, shows that the p-value is significant for Wednesday i.e. a Wednesday effect exists in the NIFTY returns. However, R^2 is 0.005 which is very low, and the F-statistic indicate that the overall fit of the model is poor. The return series exhibits autoregressive conditional heteroskedasticity (ARCH) effects and is autocorrelated at level 1 as evidenced by Table 4 and 5.

Table 4: Results of the ARCH LM Test

F-statistic	248.6846	Prob. F(1,5218)	0
Obs*R-squared	237.4627	Prob. Chi-Square(1)	0

Table 5: Breusch-Godfrey Serial Correlation LM Test

F-statistic	17.85360	Prob. F(2,5213)	0.0000
Obs*R-squared	35.51190	Prob. Chi-Square(2)	0.0000

The statistically significance of the p-values for the ARCH LM test indicates the presence of Autoregressive Conditional Heteroskedasticity in the residuals. This confirms the clustering effects in returns i.e. large shocks to the error process are succeeded by large ones and small shocks are followed by small ones of either sign.

The presence of the ARCH effects imply that ARCH-type models accounting for such heteroskedasticity component in the series are the most appropriate for modelling returns on the NIFTY 50 index. Introduced by Engle (1982), the first ARCH model was extended to account for multiple types of volatility clustering over time beginning with the Generalized ARCH (GARCH) model by Bollerslev (1986), Exponential GARCH (EGARCH) model by Nelson (1991), Asymmetric Power ARCH (APARCH) by Ding, Granger and Engle (1993) etc. The selection of the ARCH family model most relevant for the series can be done through the choice of the model with the AIC, BIC(Schwarz) information criteria that penalise the likelihood. Based on the results provided by these criteria as per Table 6, the EGARCH model has been selected. The EGARCH model as specified by Nelson (1991) accounts for the leverage effect and the asymmetric information property found in financial returns. An EGARCH (p,q) can be stated as having mean equation of

$r_t=\mu+\varepsilon_t$

such that $\varepsilon_t=\sigma_t z_t,$

where *zt* is standard Gaussian constant and the conditional variance equation is given as:

$\ln(\sigma^2{}_t) = \omega+\alpha(|z_{t-1}|-E[|z_{t-1}|])+\gamma z_t-1+\beta\ln(\sigma^2{}_{t-1})$

where

ω= constant

$\ln(\sigma^2{}_{t-1})$ = lag of the conditional variance

α = magnitude effect

γ = asymmetric or leverage effect

Further to correct the autocorrelation of the order one, an AR(1) term is added to the right side of the dummy regression model. The improved model selection and the detailed results are seen in **Table 7**. **Table 7** shows the results of the mean returns and variance equation of the EGARCH model for the day-of-the-week effect. Here, we include the Monday dummy as an explanatory variable. As seen in the table, the EGARCH (1,1) model clearly shows that the Monday dummy is still significant in the mean equation of the GARCH model. Thus, we know that the Wednesday effect cannot be explained by time varying volatility and reflects truly anomalous returns.

Table 6: Selection of appropriate ARCH model for the data set

	ARCH	**GARCH**	**TARCH**	**EGARCH**	**APGARCH**
Akaike info criterion	-5.568303	-5.728173	-5.739279	-5.740534*	-5.739
Schwarz criterion	-5.558251	-5.716864	-5.726713	-5.727969*	-5.726081
Maximum likelihood	14544.06	14962.4	14992.39	14995.66*	14994.63

Table 7: Results of EGARCH Model for day-of-the-week returns

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Monday	-0.000154	0.000325	-0.474913	0.6348
Tuesday	-0.000162	0.000375	-0.431394	0.6662
Wednesday	0.001646	0.000351	4.682807	0
Thursday	0.000387	0.000353	1.097327	0.2725
Friday	0.000327	0.000354	0.923562	0.3557

AR(1)	0.108652	0.01434	7.576684	0
	Variance Equation			
C(7)	-0.449901	0.026012	-17.29606	0
C(8)	0.22268	0.008973	24.81686	0
C(9)	-0.081184	0.006561	-12.37284	0
C(10)	0.967279	0.002784	347.4839	0
R-squared	0.008423			

To test for the seasonality in Nifty 50 return using monthly data, the equation (2) was estimated using standard OLS estimation procedure. The results for monthly returns for Nifty 50 are reported in Table 8. January has been taken as the benchmark month in the model represented by the intercept which provided negative return of -0.009 percent on an average over the study period. An examination of the corresponding p-values show that none of the coefficients are significant except December month which indicate the presence of December effect in Nifty monthly returns.

Table 8: Results of OLS estimation procedure for NIFTY 50 monthly returns

Variable	Coefficient	Std. Error	t-Statistic	P-Value
January	-0.009	0.016	-0.598	0.551
February	0.014	0.016	0.911	0.363
March	-0.002	0.016	-0.110	0.912
April	0.010	0.016	0.616	0.539
May	0.004	0.016	0.252	0.801
June	0.011	0.016	0.692	0.490
July	0.009	0.016	0.594	0.553
August	0.000	0.016	0.025	0.980
September	0.015	0.016	0.971	0.333
October	-0.011	0.016	-0.698	0.486
November	0.011	0.016	0.680	0.497
December	0.038	0.016	2.446	0.015*
R-squared	0.000011			
F-statistic	0.002768			
Prob(F-statistic)	0.95808			

As evidenced, both the R^2 and F-statistic are quite low which indicates that the overall fit of the model is poor. Also. unlike daily returns, monthly Nifty returns do not exhibit autoregressive conditional heteroskedasticity (ARCH) effects as confirmed by results of ARCH-LM test shown in Table 9. Further, the monthly returns do not exhibit autocorrelation as seen in **Table 10.**

Table 9: Results of the ARCH-LM test

F-statistic	0.002768	Prob. F(1,249)	0.9581
Obs*R-squared	0.002791	Prob. Chi-Square(1)	0.9579

Table 10: Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.588982	Prob. F(2,238)	0.5557
R-squared	1.241114	Prob. Chi-Square(2)	0.5376

CONCLUSION

In practice, efficiency of markets varies through different markets and different countries. While strong form of market efficiency is practically not observed, it has been seen that markets around the world fail to be exhibit even weak form of efficiency due to the existence of anomalies. Various reasons have been given for these anomalies such as high competition and free entry conditions. These reasons imply that while markets can be efficient to different extents, the presence of anomalies distort efficiency and create profitable ventures for participants.

On the basis of the empirical evidence presented here, the weak-form market efficiency hypothesis can be rejected in India. The results seen in the EGARCH and OLS model estimates for daily and monthly returns clearly indicate the existence of calendar anomalies in the Nifty return series In context of India, the existence of anomalies could be attributable to a number of causes. While the study does not delve into finding these causes, the existence of exploitable patterns in the stock market returns helps active investment strategy to be an important exercise in generating excess returns. As such, the investors can improve their returns by timing their investment in the Indian stock markets.

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