CALENDAR ANOMALIES IN THE INDIAN STOCK MARKETS: MONSOON EFFECT

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ABSTRACT

This paper deals with identifying the presence of monsoon effect in the Indian stock market using EGARCH model as well as the impact on the volatility of returns of the selected indices during the monsoon months in India.

Daily time series data of closing price of four major indices i.e. Nifty 50, Nifty Smallcap 100, Nifty Midcap 100 and Nifty 500 over a period of sixteen years (April 2002 to March 2018) were collected and analysed.

The results substantiate the fact that monsoon effect is present in the Indian equity market. The returns of Nifty 50 and Nifty 500 indices during the month of September were significantly higher. There was also a significant increase in the volatility during the month of September. No significant change was detected during the monsoon months for Midcap 100 and Nifty Smallcap 100. Monsoon effect was found in indices tracking top performing 50 stocks and 500 stocks listed in NSE. Hence, it can be inferred that monsoon effect is present in the Indian stock market.

Keywords: EMH, Monsoon Effect, Anomaly, ADF Test, EGARCH Models.

INTRODUCTION

The Efficient Market Hypothesis (EMH) is a vital component of the modern investment theory and thereby states that stock prices, at all instances, exhibit all the available market information. According to EMH, stocks always trade at an unbiased estimate of their intrinsic value and hence, investors cannot earn any abnormal returns. Fama describes efficient market as "*A market with large number of rational individuals, with a goal of profit maximization, avidly competing with each other and attempting to predict future market prices of individual securities, and where all relevant information is almost freely available to all investors. The security prices quickly adjust to the new information as readily that is available"* (Fama, 1970). Fama also stated that the following conditions are to be met for market efficiency.

1. Transaction costs are nil.
2. Market participants can access information freely and easily.
3. There should be complete consensus between all market participants on the implication of the available information on stock prices as well as the future distribution of stock prices.

Relevant information comprises of past, public and private information. Markets can be classified into three levels of efficiency appertaining to the availability of relevant information (Fama, 1970).

1. Weak form efficiency.
2. Semi-strong form efficiency.
3. Strong form efficiency.

The random walk hypothesis, which proclaims that stock prices fluctuate in a random and independent manner, is coherent with the weak form of market efficiency. In this form, all historical data is incorporated in the current stock prices (Marcus et al., 2011). Therefore, technical analysis cannot be used for making abnormal profits (Marcus et al., 2011). Nonetheless, fundamental analysis and insider trading can be employed to make abnormal profits.

In the semi strong form, impact of all public as well as historically available information is already integrated in current stock prices. Thus, nobody can use fundamental analysis to make extra profits (Marcus et al., 2011). However, insider trading can be used to make abnormal profits.

Whereas in the strong form, nobody can outperform the market by any means as stock prices have effectively adjusted after incorporating the impact of all available news. Thus, even private information cannot be utilized to surpass the market returns if the strong form persists (Brealey et al., 2014).

Financial Market Anomalies

The denotation of an anomaly is any deviation from the common rule, type or form. Financial market anomaly refers to any circumstance in which the performance of a stock or a portfolio varies from the postulates of EMH (Silver, 2011). Financial market anomalies can be primarily classified into three categories:

1. Calendar or seasonal anomaly.
2. Technical anomaly.
3. Fundamental anomaly.

The weak form of EMH proposes that markets efficiently incorporate the impact of past prices on current market price and any sort of analysis cannot be used for predicting future prices is contradicted by calendar anomalies. The investors can earn abnormal returns due to the presence of these anomalies which contradict the postulates of weak form of market efficiency (Boudreaux, 1995). Calendar anomalies testify that technical analysis can be utilized to identify seasonal patterns in past prices thereby opposing the weak form of EMH.

Volatility of Returns

The volatility of the returns of an asset/portfolio is used to assess the risk associated with the fluctuations in the returns of the asset. The volatility of an asset/portfolio can be measured through the variance or standard deviation between the returns of successive periods (Chou, 1988).

This study targets on analyzing the presence of monsoon effect in the returns and volatility of Indian stock market.

REVIEW OF LITERATURE

Numerous studies were conducted previously to analyze the effects of calendar anomalies on the equity markets of India as well as various other countries. The review of the previous studies made in India and abroad are listed below.

Chotigeat & Pandey (2005) investigated and proved the presence of seasonality in stock returns in SENSEX and EMAS (Kuala Lumpur Stock Exchange) index. Patel (2008) analysed BSE 500 and NSE 500, and diagnosed the presence of two separate calendar effects. First of all, a November-December effect, where the mean returns in the month of November and December considerably exceeded the returns of the leftover months. Furthermore, the presence of March to May effect, where the mean returns of March-May were considerably lesser than those of the leftover months. Archana et al. (2014) stated that Turn of the Month Effect and Turn of the Year Effect were minimally visible in the Indian equity market but, not statistically proven for the analysed period. Whereas, Chandra (2009) confirmed the presence of Turn of the Month Effect and Time of the Month Effect in BSE-SENSEX and statistically significant values were observed for both the effects. Kumar (2017) investigated for the presence of January Effect, Day of the Week Effect and Turn of the Month Effect and concluded by stating that such anomalies will eventually disappear from the market with progress in information technology and systematized currency markets operational round the clock, ultimately reducing the cost of information. Similarly, Caporale & Zakirova (2017) reported that all anomalies disappear if transaction costs are taken into account thus, suggesting that no investor can make abnormal profits by any means.

Agrawal & Tandon (1994) examined five seasonal patterns i.e. Month of the Year Effect, Turn of the Month Effect, Holiday/December end Effect, Day of the Week Effect and Friday the thirteenth Superstition Effect in Eighteen Countries. They reported the presence of Day of the Week Effect in nine out of eighteen countries, Turn of the Month Effect in fourteen countries. The Month of the Year Effect was also found in fourteen countries. Gregoriou et al. (2008) analysed returns of three indices i.e. S&P CNX Defty, S&P CNX Nifty and CNX Nifty Junior. Their outcome substantiates lower returns on Mondays and Fridays and they suggest a strategy that the investors could implement to earn abnormal returns. Mitra & Khan, (2014) investigated the Day of the Week Effect in NSE Nifty 50 and found no such anomaly in all but one model in which the index exhibits Wednesday effect on intraday return of the index. Whereas, Kaushik (2017) scrutinized for presence of day-of-the-week effect on returns of BSE Smallcap, Midcap and Largecap indices of Indian capital market using GARCH model and confirmed the presence of Day of the Week effect only in BSE Smallcap

Hooi et al. (2007) examined the existence of January effect and Day of the Week effect in the equity markets of Japan, Taiwan, Singapore, Hong Kong, Malaysia, Indonesia, and Thailand and reported that Day of the Week effect is present in some Asian markets but proposes that the January effect has mostly disappeared. Patel (2014) and Qureshi & Hunjra, (2015) contradict the presence of anomalies in Indian and Pakistani stock markets respectively and state that their analysis is consistent with the efficient market theory. Whereas, Sharma et al. (2014) confirmed the presence of the Month of the Year anomaly in the Indian equity markets. Additionally, Kumar & Jawa (2016) and Gupta (2017) also confirm that December Effect is present in the Indian stock markets, thereby implying the presence of informational inefficiency in Indian stock markets.

Ariel (1990) investigated the pattern of daily stock returns on trading days preceding the holidays so as to analyze whether trading days prior to holiday would give high returns. The outcome of this study confirmed that returns on the trading day prior to holidays are significantly high and equal to nine to fourteen times of the returns accruing on other days. Whereas**,** Marrett & Worthington (2007) applied a Regression based approach to study holiday effect in the Australian daily stock returns at three different levels and the results showed significant pre-holiday effect in terms of returns. It is also observed that the returns for the retail industry stocks are high compared to other industries on the trading day prior to holidays.

Vachhrajani et al. (2014) and Desai & Joshi (2018) examined the presence of Monsoon Effect in the stock markets of India. Although they validate the existence of Monsoon Effect, i.e. the post-monsoon period returns were significantly higher than that of the pre-monsoon period, but the regression model used by them was not appropriate as they did not introduce constant variable in the mean equation of the regression model, resulting in inadequate results.

RESEARCH GAP

Albeit, many researches have been conducted to examine the persistence of anomalies in the Indian stock market, there is not much thorough study about the effects of monsoon on the Indian stock market. Hence, it becomes viable to study the effect of such anomaly in the Indian stock market and analyze if any abnormal returns can be generated by trading on strategies based on this anomaly.

STATEMENT OF THE PROBLEM

The Efficient Market Hypothesis (EMH) primarily says that markets efficiently process and exhibit the impact of all available information, hence, no investor can make abnormal returns. However, as seen through the review of existing literature, various anomalies like Month of the Year Effect, Day of the Week Effect, Holiday Effect etc. have been found in the Indian stock market. Presence of such anomaly enables investors to strategize and make abnormal profits. Therefore, examining the existence of anomaly would help investors make strategies for investment in securities.

The focal point of this study is to analyze the existence of Monsoon Effect in the Indian stock market and examine whether these anomalies can be used to build trading strategies to earn abnormal profits.

OBJECTIVES

1. To inquire the presence of calendar anomalies in the returns of the selected indices during the monsoon months.
2. To inquire the presence of calendar anomalies in the volatility of the selected indices during the monsoon months.

METHODOLOGY

Data Selection

Stock markets of India are one among the many dynamic bourses of Asia. One of the two national level stock exchanges operating in India is the National Stock Exchange (NSE).

To analyze if the Monsoon Effect is present in the Indian Stock market, the following four indices have been selected keeping in mind the various groups of stocks listed in NSE.

1. NIFTY 50-represents top 50 blue-chip companies.
2. NIFTY 500-represents the top 500 companies based on full market capitalization.
3. NIFTY MIDCAP 100-represents midcap companies.
4. NIFTY SMALL CAP 100-represents smallcap companies.

Period of Study

This study attempts to identify the monsoon effect in the chosen indices representing the Indian stock market during the Post Rolling Settlement Period from April 2002 to March 2018 (for Nifty Smallcap 100 from its launch date i.e. 1st January 2004) covering sixteen years.

"*The Compulsory Rolling Settlement System*" was introduced by NSE on January 02, 2002. The introduction of rolling settlement leads to high turnover and creates impact on the anomalous behavior of stock prices (Nageswari & Selvam, 2011). Against this background, the presence of monsoon effect in the chosen indices returns and volatility was investigated in this study.

Data Analysis

To study the Monsoon Effect in the returns of the selected indices, returns were calculated as per the following formula:

$$R_t = \log(P_t) - \log(P_{(t-1)}) \quad (1)$$

Where, R_t is the daily return of selected indices at time t. P_t denotes the closing price of the index at time period t, and $P_{(t-1)}$ denotes the closing price of the index at time period t-1. For analyzing the data, Augmented dickey-fuller test, EGARCH Model and ARCH LM Test were used.

EMPIRICAL RESULTS

Descriptive Statistics

Table 1
DESCRIPTIVE STATISTICS OF RETURNS OF SELECTED INDICES

	Nifty 50	Nifty 500	Nifty Midcap 100	Nifty Smallcap 100
Mean	0.000548	0.000610	0.000739	0.000580
Median	0.000948	0.001502	0.002175	0.002236
Std. Dev.	0.014255	0.014246	0.015298	0.013929
Skewness	-0.271157	-0.536118	-0.962813	-1.178362
Kurtosis	13.81247	11.48520	10.61260	13.42259
Jarque-Bera (Prob.)	19446.03 (0.000000)	18214.35 (0.000000)	12561.01 (0.000000)	9364.453 (0.000000)

Table 1 shows the descriptive statistics for daily returns of the selected indices. Nifty 50 has the lowest mean returns whereas Nifty Midcap 100 has the highest mean returns. In addition to that Nifty Midcap 100 also has the highest standard deviation thus conforming to the expectation that higher returns lead to higher risk and vice versa. The data for all indices were left tailed as the skewness is negative, it was also noted that the data is heavily tailed commonly termed as Leptokurtic, as Kurtosis values are positive and lie between 10.5 to 13.5 for all the indices. The returns of the selected indices are not normally distributed as the computed p-values of the Jarque-Bera test were significant at 5%.

Results of Augmented Dickey Fuller-Unit Root Test

Augmented Dickey-Fuller (ADF) Unit Root test was applied to the returns of the selected indices. Non-stationary data leads to spurious results, therefore it becomes mandatory to perform this test in order to analyze the stationarity of data before any further analysis. (Dickey & Fuller, 1979)

The null hypothesis (H_0) of this test is that the chosen time series data has a unit root. The H_0 was rejected for all the chosen indices as the respective p-values were lower than 0.05, which proves that returns of the chosen indices were stationary at level. The estimates of the test (t-statistic and respective p-values) are shown in Table 2.

Table 2
ADF-UNIT ROOT TEST FOR SELECTED INDICES (AT LEVEL)

Index Returns	T-Statistic	Prob.
Nifty 50	-58.76886	0.0001

Table 2 ADF-UNIT ROOT TEST FOR SELECTED INDICES (AT LEVEL)		
Nifty 500	-56.27894	0.0001
Nifty Midcap 100	-52.69138	0.0001
Nifty Smallcap 100	-48.15245	0.0001

Estimation of EGARCH Model

After stationarity test, EGARCH model was estimated to investigate the presence of market anomalies in the index returns. GARCH family models are better than OLS in analysing data where the variances of the error terms are unequal i.e. the data is heteroskedastic. These models help to identify the features of volatility in the returns of the selected indices. (Engle, 2001). OLS, GARCH, TGARCH, EGARCH and PGARCH models were estimated and the model with lowest values of AIC, SC and HQC criterions was selected.

The following EGARCH model was estimated for the analysis.

$$R_t = \beta_0 + \beta_1 June + \beta_2 July + \beta_3 August + \beta_4 September + \varepsilon_t \qquad (2)$$

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}} \qquad (3)$$

In the equation (2), R_t denotes the returns of the chosen index. β_0 represents the constant. Dummy variables for the four monsoon months i.e. June-September were introduced in the mean equation of the regression model, to investigate the presence of any anomaly in the mean returns. The coefficients for the respective dummy variable would estimate the magnitude of the abnormal returns for each of the month chosen for the study. If the estimated coefficient for any dummy variable is significant, then it will support the presence of anomalies in the returns of the respective index concerned.

In equation (3),ω refers to the constant of the variance equation, $\beta \log(\sigma_{t-1}^2)$ is the GARCH term which estimates the magnitude of clustering effect in the conditional volatility of the chosen index returns. $\alpha \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|$ is the ARCH term which estimates the presence and magnitude of ARCH effect in the estimated conditional variance. $\gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}}$ is the asymmetric term which estimates the magnitude of asymmetric effect. Asymmetric term measures the magnitude of asymmetric effect in the conditional variance of the chosen index return. Negative innovation, generally leads to a higher next period volatility compared to positive innovation. This feature is known as Asymmetric effect (Ding et al., 1993). The estimated EGARCH model coefficients with associated z statistics and p-values are shown in Table 3 and Table 4.

ARCH LM Test

ARCH LM test was applied to investigate the presence of ARCH type of heteroskedasticity in the residuals of the EGARCH model. The null hypothesis for the ARCH LM test is that the residuals of the EGARCH model do not suffer from ARCH type of heteroskedasticity. The results of the ARCH LM test are presented along with model estimations in Tables 3 and 4.

The EGARCH models for Nifty 50 and Nifty 500, displayed in Table 3, were estimated by introducing AR (1) term in the mean equation of the model in order to correct the autocorrelation present in residuals of the mean equation. Autocorrelation in residuals would make the estimated test statistics and p-values less reliable (Bhattacharya et al., 2003).

Table 3 EGARCH MODEL						
	Dependent Variable-Nifty 50			Dependent Variable-Nifty 500		
	Coeff.	**z-stat.**	**Prob.**	**Coeff.**	**z-stat.**	**Prob.**
Mean Equation						
C	0.000403	1.969987	0.0488	0.000511	2.339991	0.0164
June	-7.11E-05	-0.11560	0.9080	-0.00014	-020090	0.8408
July	0.000304	0.540981	0.5885	0.000127	0.213112	0.8312
August	-1.10E-05	-0.02132	09830	-2.45E-05	-0.04182	0.9666
September	**0.001302**	**2.574163**	**0.0100**	**0.001211**	**2.055460**	**0.0398**
AR (1)	0.095810	5.719363	0.0000	0.137651	7.874824	0.0000
Variance Equation						
C	0.028172	-13.0098	0.0000	-0.43498	-14.7399	0.0000
ARCH term	0.011382	17.91987	0.0000	0.227046	17.28072	0.0000
GARCH term	0.002551	382.6837	0.0000	0.970667	367.1687	0.0000
Asymmetry term	0.007281	-12.0459	0.0000	-0.09018	-12.1250	0.0000
ARCH LM Test						
		R-Squared	Prob.		R-Squared	Prob.
		0.291697	0.5892		0.205062	0.6508

The estimated ARCH terms for the EGARCH model of Nifty 50 and Nifty 500 indices were significant at 5% level. The estimated GARCH terms for the EGARCH model of Nifty 50 and Nifty 500 indices were significant at 5% level. This result can be interpreted that the conditional volatility of the chosen indices has strong clustering feature which would result in persistence of volatility.

The estimated Asymmetric term for the EGARCH model of Nifty 50 and Nifty 500 indices were significant at 5% level. The coefficient of the Asymmetric term was negative indicating that bad news or negative innovation increases the volatility of the next time period compared to good news.

The estimated coefficient of the dummy variable representing the month of September for Nifty 50 and Nifty 500 indices were significant at 5% level. This indicates that statistically significant positive returns were observed during the month of September for Nifty 50 and Nifty 500 indices. If the market returns are significantly higher for any specific month, it is considered as a calendar anomaly. Presence of this calendar anomaly would make it possible for the investors to earn super normal profits by exploiting this anomaly.

The p-values for the test statistic of ARCH LM test were insignificant at 5% level for Nifty 50 and Nifty 500 indices indicating that the residuals are free from ARCH type of heteroskedasticity, which proves that EGARCH model is a good fit for the chosen indices.

Table 4 EGARCH MODEL						
	Dependent Variable-Nifty Midcap 100			Dependent Variable-Nifty Smallcap 100		
Variables	**Coeff.**	**z-stat.**	**Prob.**	**Coeff.**	**z-stat.**	**Prob.**
Mean Equation						
C	0.000585	2.220892	0.0264	0.000870	2.738848	0.0062
June	-0.00030	-0.36119	0.7180	-4.99E-05	-0.05294	0.9578
July	-0.00025	-0.34226	0.7321	-0.00049	-0.53873	0.5901
August	7.30E-05	0.109873	0.9125	0.000418	0.535323	0.5924
September	0.000766	1.374575	01693	0.000450	0.555729	0.5784
AR (1)	0.198355	12.69385	0.0000	0.220901	13.51222	0.0000
Variance Equation						
C	-0.66263	-15.8017	0.0000	-0.904603	-15.8283	0.0000
ARCH term	0.266153	18.3775	0.0000	0.293428	22.38660	0.0000
GARCH term	0.947681	222.5948	0.0000	0.921615	147.3566	0.0000

Table 4 EGARCH MODEL						
Asymmetry term	-0.084086	-10.4006	0.0000	-0.104492	-12.1614	0.0000
ARCH LM Test						
		R-Squared	Prob.		R-Squared	Prob.
		0.720161	0.3962		0.013153	0.9087

The EGARCH models for Nifty Midcap 100 and Nifty Smallcap 100, displayed in Table 4, were estimated by introducing AR (1) term in the mean equation of the model in order to correct the autocorrelation present in residuals of the mean equation.

The estimated ARCH terms for the EGARCH model of Nifty Midcap 100 and Nifty Smallcap 100 indices were significant at 5% level. The estimated GARCH terms for the EGARCH model of Nifty Midcap 100 and Nifty Smallcap 100 indices were significant at 5% level. This result can be interpreted that the conditional volatility of the chosen indices has strong clustering feature which would result in persistence of volatility.

The estimated Asymmetric term for the EGARCH model of Nifty Midcap 100 and Nifty Smallcap 100 indices were significant at 5% level. The coefficient of the Asymmetric term was negative indicating that bad news or negative innovation increases the volatility of the next time period compared to good news.

None of the estimated coefficients of the dummy variables representing the monsoon months for Nifty Midcap 100 and Nifty Smallcap 100 indices were significant at 5% level. This validates that abnormal profits cannot be earned during monsoon months for Nifty Midcap 100 and Nifty Smallcap 100 companies. The results for Nifty Midcap 100 and Nifty Smallcap 100 are inconsistent with that of Nifty 50 and Nifty 500 which verifies that there is no calendar anomaly present in the market returns for Midcap and Smallcap companies during the study period.

The p-values for the test statistic of ARCH LM test were insignificant at 5% level for Nifty 50 and Nifty 500 indices indicating that the residuals are free from ARCH type of heteroskedasticity, which proves that EGARCH model is a good fit for the chosen indices.

To further understand the impact of monsoon on the volatility of chosen indices, the dummy variables for four months of monsoon were introduced in the variance equation of the EGARCH model and the results are presented in Table 5.

Table 5
VARIANCE EQUATION-IMPACT ON VOLATILITY

	Nifty 50		**Nifty 500**		**Nifty Midcap 100**		**Nifty Smallcap 100**	
Variables	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff**	**Prob.**
C	-0.361820	0.0000	-0.427287	0.0000	-0.65078	0.0000	-0.894937	0.0000
ARCH Term	0.203704	0.0000	0.225268	0.0000	0.266456	0.0000	0.291564	0.0000
Asymmetric Term	-0.086002	0.0000	-0.087508	0.0000	-0.08280	0.0000	-0.104029	0.0000
GARCH Term	0.976903	0.0000	0.971365	0.0000	0.949070	0.0000	0.922497	0.0000
June	-0.012020	0.1985	-0.015417	0.1246	-0.015645	0.2341	-0.015387	0.3184
July	-0.002497	0.7496	-0.007154	0.4115	-0.014800	0.2031	-0.022664	0.0905
August	0.004580	0.5504	0.004262	0.5789	0.016049	0.0352	0.015656	0.1844
September	0.020207	0.0137	0.016840	0.0380	0.014154	0.1004	0.014467	0.1339

The presence of the calendar anomaly was examined by introducing time dummy variables in to the variance equation of EGARCH model of all the chosen indices. The coefficients of all the time dummy variables were insignificant at 5% level except for the month of September for Nifty 50 and Nifty 500 indices. But for Nifty midcap 100 and Nifty small cap 100, coefficients of all the time dummy variable were insignificant at 5% level.

These results can be interpreted that the market anomalies were present in stock market return and volatility for Nifty 50 and Nifty 500, but the evidence in the other indices was inconclusive. The results suggest that the calendar anomalies were present only in the shares which are highly liquid and that belong to top performing NSE listed companies.

CONCLUSION

This study examined the presence of monsoon effect (Calendar anomaly) in the returns and volatility of Indian stock market. Four stock market indices were chosen for the study to cover different combinations of stocks in the market. Strong clustering and asymmetric effect were found for all the chosen indices, which means that the stock market volatility in India is highly clustered and this would lead to high persistence in volatility. The results also support the fact that the returns and volatility were higher during the month of September in Indian stock market during the study period. This in turn leads us to deduce that monsoon effect is present in Indian stock market.

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