

## Day-of-the-Week Effects in the Indian Stock Market

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### ABSTRACT

This paper investigates empirically the day-of-the-week effect on stock returns and volatility of the Indian stock markets. The GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models were employed to examine the existence of daily anomalies over the period of 1<sup>st</sup> July, 1997 to 29<sup>th</sup> June, 2012. The empirical results derived from the GARCH models indicate the existence of day-of-the-week effects on stock returns and volatility of the Indian stock markets. The study reveals positive Monday and Wednesday effects in the NSE-Nifty and BSE-SENSEX market returns. The average return on Monday is significantly higher than the average return of Wednesday in the NSE-Nifty and BSE-SENSEX markets. Besides, the findings confirm the strong support of ARCH and GARCH effects persist in the returns series. Moreover, the asymmetric GARCH models show that the Indian stock market returns exhibit asymmetric (leverage) effect. Most importantly, the empirical results indicate that Tuesday effects have negative impact on volatility after controlling the persistence and asymmetric effects.

**Keywords:** Day-of-the-week Effect, Weak-form Efficiency, GARCH Models, Asymmetric Effect

**JEL Classification:** C22, G14, O53

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Any remaining errors or omissions rest solely with the author(s) of this paper.

## INTRODUCTION

The efficient market hypothesis (EMH) postulates that stock prices must efficiently reflect all available information about their intrinsic value. According to the EMH, stocks always trade at their fair value on stock exchanges, making it impossible for investors to either purchase undervalued stocks or sell stocks for inflated prices. As such, it should be impossible to outperform the overall market through expert stock selection or market timing, and that the only way an investor can possibly obtain higher returns is by purchasing riskier investments. The opponents of efficient market theory asserts that stock prices are largely determined based on investor expectation, and that price movements will follow any patterns or trends and that past price movements can be used to predict future price movements. Besides, the efficient market hypothesis was contradicted by anomalies such as calendar anomalies, fundamental anomalies and technical anomalies. Calendar anomalies refer to the tendency of securities to behave differently on a particular day-of-the-week, or month-of-the-year. Among such anomalies, the day-of-the-week effect has been seen as one of the most important patterns and it has been found in several emerging stock markets (French, 1980; Jaffe and Westerfield, 1985; Balaban, 1995; Lian and Chen, 2004). The day-of-the-week effect indicates that returns are abnormally higher on some days of the week than on other days. Specifically, results derived from many empirical studies have documented that the average return on Friday is abnormally high, and the average return on Monday is abnormally low. Besides, the rational investor should consider the risk or volatility of returns while making of investment decisions. It is expected that there exist significant differences in volatility across day of the week in stock markets.

The day-of-the-week effects have been significantly documented in the financial literature in the context of both developed and emerging stock-markets. It has become a challenge to the EMH and attracts much attention from economists, market regulators, market practitioners and investors. Examination of day-of-the-week effects is immense helpful for rational decision-makers to be sentient of variation in the volatility of stock returns dependent on the day-of-the week and whether high or low returns are associated with a correspondingly high or low volatility for a given day. If investors can identify a certain pattern of volatility, it is easier to make investment decisions based on both the projected returns and the risks associated with the particular security. Besides, the investigation of anomalous patterns may reveal evidence about the extent of market efficiency.

This paper aims to investigate empirically the day-of-the-week effect on stock returns and volatility of the Indian stock markets. The remainder of the article is organised as follows: Section-II provides review of related literature. Section-III

describes the methodology and data used for empirical analysis. Section-IV offers empirical results and discussion of the study. Concluding remarks are presented in section-V.

## REVIEW OF LITERATURE

Empirical studies of the US stock market such as French (1980) and Gibbon and Hess (1981) found that the mean return is significantly negative on Monday, but it is significantly positive on Friday. Jaffe and Westerfield (1985) examined daily returns in the emerging stock market of Japan, Canada, Australia, the UK and the US. They found significant negative returns on Monday in the US, Canada and the UK, and on Tuesday for Japan and Australia, while a positive Friday effect was found in all the markets except the UK. Solnik and Bousquet (1990) examined the day-of-the-week effect for Paris Bourse and found strong and persistent negative return on Tuesday, which is in line with the findings of Barone (1990) for the Italian Stock Market. Wong et al. (1992) examined the days-of-the-week in the stock market returns of five Asian countries for the period 1975–1988. They found a significantly negative Monday effect in Singapore, Malaysia and Hong Kong. Further, they reported a negative Tuesday effect in Thailand, and a positive Friday effect in the four markets. Balaban (1995) investigated the day-of-the-week effects on the stock market returns of Istanbul Securities Exchange and found a significant positive Wednesday and Friday effect, and that Monday was the most volatile day for stock returns. Wong and Yuanto (1999) found a significant negative effect on Tuesdays and a positive effect on Fridays in the daily stock market returns of Indonesia. Using Autoregressive Moving Average (ARIMA) model, Mookerjee and Yu (1999) observed significant positive Thursday and Friday effects in the Shanghai securities exchange, but no day-of-the-week effect was found in the Shenzhen securities exchange. By and large, these studies have used measures of central tendency, conventional regression approach and ARIMA models to investigate the seasonal anomalies or day-of-the-week patterns in mean returns of the emerging stock markets. However, none of these studies has investigated day-of-the-week effect in stock market volatility. Many empirical studies have indicated persistent and potentially exploitable day-of-the-week patterns in stock returns of various economies. It is necessary for rational decision-makers to be aware of variations in the volatility of stock returns dependent on the day-of-the-week and whether high or low returns are associated with a correspondingly high or low volatility for a given day. If investors can identify a certain pattern of volatility, it is easier to make investment decisions based on both the projected returns and the risks associated with the particular security (Kiymaz and Berument, 2003). Accordingly,

several empirical studies investigated the time series behavior of stock prices in terms of volatility by using variations of the generalized autoregressive conditional heteroscedasticity (GARCH) models. Choudhry (2000) studied for seven emerging Asian stock markets that include India, Indonesia, Malaysia, Philippine, South Korea, Taiwan, and Thailand. The empirical findings proved a presence of the day-of-the-week effect on both returns and volatility. Al-Loughani and Chappell (2001) employed the GARCH model on Kuwait stock market and found that returns were higher on Friday and lower on Monday providing supportive evidence of the day-of-the-week effect. Chusanachoti and Kamath (2002) investigated the Thailand stock market and found significant Monday, Tuesday, Thursday and Friday effects. Moreover, Kiymaz and Berument (2003) found evidence of the day-of-the-week effect in both returns and volatility of emerging stock markets. They observed significant Monday's effect for Germany and Japan, Friday's effect for Canada and the United States, and Thursday's effect for the UK. Besides, Ajayi et al. (2004) found evidence of the day-of-the-week effect in four out of eleven stock markets that includes Estonia, Lithuania, Russia and Slovenia. They observed the significant negative Monday effect in Estonia and Lithuania while positive Monday and Friday effects in Russia and Slovenia, respectively. Besides, Lian and Chen (2004) analysed the calendar behaviour of Vietnamese stock market and found significant positive returns on Friday. The empirical results consistently indicated a significantly negative mean return on Tuesday and Thursday, but no seasonal pattern in return volatility. Gregoriou et al. (2004) examined the stock returns of the UK stock market utilizing the FTSE 100 index. The empirical results provide evidence of the no day-of-the-week effect, suggesting that the UK stock market appears to be weak-form efficient. Similarly, Aly et al. (2004) found no evidence of daily seasonality in the Egyptian stock market. Contrary results were obtained by Al-Rajoub (2004) on Amman stock exchange. He found significant Thursday and Monday effects on returns.

For Turkey, the study by Dicle and Hassan (2007) showed that returns on Mondays were negative and significant while returns on Thursdays and Fridays were significantly positive. Similar results were obtained by Chukwuogor-Ndu (2007) who tested the East Asian financial markets. Besides, they found insignificant daily returns and volatility in most of these markets. For the Canadian stock market, Baker et al. (2008) found that the day-of-the-week effect is sensitive in both the mean and the conditional volatility. Similarly, for the Russian stock market, McGowan and Ibrihim (2009) found significant day-of-the-week effects.

Al-Mutairi (2010) found evidence of presence of the day-of-the-week effect in Kuwait stock exchange. The empirical findings showed that Saturday returns were positive and higher than other days of the week except for Wednesday, suggesting

that Kuwait stock market is inefficient. Hussain et al. (2011) analyzed the day-of-the-week effect on the Karachi stock exchange and revealed significant Tuesday effects. Ulussever et al. (2011) studied the Saudi stock exchange and provided evidence of the presence of the day-of-the-week effect in the daily return. More recently, Abdalla (2012) explored the calendar anomalies of Khartoum stock exchange (KSE). The empirical findings revealed no evidence of day-of-the-week effect on stock market returns and volatility.

By examining the day of the week effect in Indian stock market, Ignatius (1992) confirmed the existence of a weak form of the week-end effect in the Indian market for the period of 1979-1990. Agarwal and Tandon (1994) found that returns were significantly negative on Mondays and Tuesdays and significant positive returns on Fridays in nine emerging countries. Poshakwale (1996) for the Indian Bombay stock exchange (BSE), showed that returns on Fridays were significantly higher compared with other days of the week. Goswami and Anshuman (2000) studied the Week-End Effects by using equally weighted portfolio constructed from 70 stocks listed on the BSE. The study evidenced excess positive returns on Friday and excess negative returns on Tuesday. Choudhry (2000) examined the Asian emerging markets, including India, and reported significant positive Friday returns in the Indian stock market for the period January 1990 to June 1995. Bhattacharya et al. (2003) examined the day of the week effect in returns and its volatility in the Indian capital market and found significant positive returns on Monday. Nath and Dalvi (2004) examined empirically the day of the week effect anomaly in the Indian equity market for the period from 1999 to 2003 using both high frequency and end of day data for the benchmark Indian equity market index of S&P CNX NIFTY. The study found that before the introduction of rolling settlement, Monday and Friday were significant days. However, after the introduction of the rolling settlement, Friday has become significant. Kumari and Mahendra (2006) studied the day-of-the-week effect in the Bombay Stock Exchange and the National Stock Exchange and found evidence of negative returns on Tuesday and relatively higher returns on Monday. Chander, et al. (2008) employed regression analysis and documented evidence on the day of the week effect in Indian stock markets and provided positive return on Friday and negative returns on Monday. Besides, Elango and Al-Macki (2008) studied the day-of-the-week effect in the NSE and showed Monday effect with lowest daily returns and Wednesday effect with highest daily returns. Chia and Liew (2010) examined the existence of day-of-the-week effect and asymmetrical market behavior in the Bombay Stock Exchange (BSE). They found significant positive Monday effect and negative Friday effect. Recently, Using the Kruskal-Wallis test, Patel and Patel (2011) explored the day of the week effect on stock returns in Bombay Stock Exchange. Their results do not support the

existence of the day-of-the-week effect. Recently, Pathak (2013) analysed the stock market seasonality effect in Indian stock market for the S&P CNX NIFTY (NSE) over the period from 1st April 2002 to 31st March 2012 and found non-existence of the day effect in Indian stock market.

The related literature pertaining to day-of-the-week effects are well established in the context of both developed and emerging stock markets. However, the empirical studies conducted across markets provide differing evidence over the period of time. This might be due to time-varying nature of the stock market returns and significant volatility clustering. One of the best known stylized features of financial asset returns is volatility clustering. That is, a high (or low) volatility movement is observed to be followed by a high (or low) volatility movement. The technical term given to this behaviour is autoregressive conditional heteroscedasticity (ARCH). This volatility clustering captures the dynamics of volatility variation of financial assets. Modeling this volatility clustering of a financial asset is important since volatility values can directly impact prices of options and risks of stocks and portfolios. Engle (1982, 2000), Bollerslev (1986), Nelson (1991) and Zakoian (1994) have proposed (G)ARCH-family models, which has been shown to be capable of capturing conditional volatility parsimoniously. Empirically, the family of GARCH (generalized ARCH) models has been very successful in describing the financial data and are often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (see the survey by Bollerslev, Ray and Kenneth, 1992). While answering the skeptics, Andersen and Bollerslev (1998) and Verbeek (2004) claimed that the GARCH models did provide the most accurate forecasts. Besides, the asymmetric GARCH type models sufficiently captures the asymmetric response of volatility to news, whereby the conditional variance tends to respond asymmetrically to positive and negative shocks in errors. This indicates that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. Two explanations for asymmetric responses have been put forward. The traditional explanation for this phenomenon was the so-called leverage effect whereby a fall in stock price results in rise in its debt-to-equity ratio and thereby results in greater financial leverage and leading to an increase in risk premiums (Black, 1976 and Christie, 1982). Moreover, Black (1976) acknowledged that financial leverage alone was not a sufficient explanation to account for the actual size of the observed asymmetries, and an alternative explanation based on market dynamics and the role of noise traders have been expounded (Kyle, 1985 and Sentana and Wadhvani, 1982).

To address these stylized facts of return series of Indian stock markets, this paper studies the GARCH model by Bollerslev (1986), the Exponential GARCH

(EGARCH) model of Nelson (1991) and a special case of the Threshold GARCH (TGARCH) model by Glosten, Jaganathan and Runkle (1993) and Zakoian (1994) to investigate empirically the day-of-the-week effect on stock returns and volatility of the Indian stock markets.

## METHODOLOGY

### Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The standard GARCH ( $p, q$ ) model was introduced by Bollerslev (1986) that suggests the conditional variance of returns is not only dependent on the squared residuals of the mean equation but also on its own past values. The standard GARCH model captures the volatility clustering of financial time series. Hence, by using an appropriate GARCH model, while controlling for time-varying property of volatility, one can estimate the changes in the information flows, i.e., the impact of recent and old news on volatility. Specifically, Log likelihood ratio tests on the GARCH model for  $p, q \in \{1, 2, \dots, 5\}$  are employed in order to find the most parsimonious GARCH representation of the conditional variance of returns. A GARCH ( $p, q$ ) process is represented as:

$$R_t = \alpha_1 R_{t-1} + \sum_{i=1}^5 \lambda_i D_{it} + \varepsilon_t \quad (1)$$

$$h_t = \omega_1 + \sum_{i=1}^p \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^q \delta_j h_{t-j} + \sum_{i=1}^4 \lambda_i D_{it} \quad (2)$$

where, equations (1) and (2) denote the conditional mean equation and the conditional variance equation respectively.  $R_t$  is the spot returns of the S&P CNX Nifty and SENSEX indexes at time 't'.  $R_{t-1}$  is a proxy for the mean of  $R_t$  conditional on past information.  $h_t$  is the conditional variance of the period t. Only four out of five days in the week are included in the conditional variance equation to avoid the dummy variable trap in the regression model. Thus,  $D_{it}$ 's ( $i = 1, 2, \dots, 4$ ) are dummy variables for Monday, Tuesday, Thursday and Friday, respectively (Wednesday is excluded) (Loc, 2006). The GARCH (1,1) is weakly stationary if  $\alpha_i + \delta_1 < 1$ ,  $\alpha_i$  and  $\delta_1$  are non-negative,  $\alpha_i$  (ARCH parameter) represents the news about volatility from the previous period and  $\delta_1$  (GARCH parameter) represents a persistence coefficient. If the sum of ARCH and GARCH coefficients ( $\alpha + \delta$ ) is very close to one, the volatility shocks are very persistent. It is an indication of a covariance stationary model with a high degree of persistence and long memory in the conditional variance.

The basic GARCH is symmetric and does not capture the asymmetry effect that is inherent in most stock markets return data also known as the “leverage effect”. In the context of financial time series analysis the asymmetry effect refers to the characteristic of times series on asset prices that ‘bad news’ tends to increase volatility more than ‘good news’ (Black, 1976 and Nelson, 1991). The Exponential GARCH (EGARCH) model and the Threshold GARCH (TGARCH) model proposed by Nelson (1991) and Glosten, Jagannathan and Runkle (1993) respectively are specifically designed to capture the asymmetry shock to the conditional variance.

### Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

Nelson (1991) proposed Exponential GARCH model which allows the conditional volatility to have asymmetric relation with past data. Statistically, this effect occurs when an unexpected drop in stock price due to bad news increases volatility more than an unexpected increase in price due to good news of similar magnitude. This model expresses the conditional variance of a given variable as a non-linear function of its own past values of standardised innovations that can react asymmetrically to good and bad news (Drimbetas, Sariannidis and Porfiris, 2007). Specifically, Log likelihood ratio tests on an EGARCH model for  $p, q \in \{1, 2, \dots, 5\}$  are employed in order to find the most parsimonious EGARCH representation of the conditional variance of returns. The EGARCH (1,1) model can be specified as follows:

$$R_t = a_1 R_{t-1} + \sum_{i=1}^5 \lambda_i D_{1it} + \varepsilon_t \quad (3)$$

$$\ln(\sigma_t^2) = \omega_1 + \delta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=1}^4 \lambda_i D_{it} \quad (4)$$

where,  $\sigma_{t-1}^2$  denotes the estimation of the variance of the previous time period that stands for the linkage between current and past volatility. In other words, it measures the degree of volatility persistence of conditional variance in the previous period.  $\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right|$  represents information concerning the volatility of the previous time period. It signifies the magnitude impact (size effect) coming from the unexpected shocks.  $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$  indicates information concerning the leverage ( $\gamma_1 > 0$ ) and the asymmetry ( $\gamma_1 \neq 0$ ) effects.  $\delta_1, \alpha_1$  and  $\gamma$  are the constant parameters to be estimated. The parameters,  $\lambda_i$ 's are employed to capture the daily effects.



$\varepsilon_t$  represents the innovations distributed as a Generalised error distribution (GED), a special case of which is the normal distribution (Nelson, 1991).

### Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) Model

The Threshold GARCH model (TGARCH) was introduced by Glosten, Jaganathan and Runkle (1993) that captures asymmetric in terms of negative and positive shocks and adds multiplicative dummy variable to check whether there is statistically significant different when shocks are negative. In TGARCH model, it has been observed that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to a “leverage effect” (Black, 1976). In the same sense, negative shocks are followed by higher volatility than positive shocks of the same magnitude (Engle and Ng, 1993). The conditional variance for the simple TGARCH model is defined by;

$$R_t = \alpha_1 R_{t-1} + \sum_{i=1}^5 \lambda_i D_{it} + \varepsilon_t \quad (5)$$

$$\sigma_t^2 = \omega_1 + \delta_1 \sigma_{t-1}^2 + \alpha_1 u_{t-1}^2 + \gamma_1 u_{t-1}^2 d_{t-1} + \sum_{i=1}^4 \lambda_i D_{it} \quad (6)$$

where,  $d_t$  takes the value of 1 if  $u_{t-1}$  is negative, and 0 otherwise. So “good news” and “bad news” have a different impact. If  $\gamma > 0$  the leverage effect exists and news impact is asymmetric if  $\gamma \neq 0$ . Notably, the additional parameters,  $\lambda_i$ 's are employed to capture the daily effects. Finally, to choose the volatility model that models best the conditional variance of the S&P CNX Nifty and SENSEX returns series, the Ljung-Box Q statistics on the squared standardized residuals and the Lagrange Multiplier (ARCH-LM) test are used.

The daily closing prices of two major indexes of Indian stock exchanges, viz., S&P CNX Nifty and the SENSEX indexes of NSE and BSE respectively were used for the study. The database was considered from 1<sup>st</sup> July, 1997 to 29<sup>th</sup> June, 2012, comprising a total of 3,748 observations. The PROWESS online database maintained by the Centre for Monitoring Indian Economy (CMIE) provides information regarding the daily closing values of the NSE S&P CNX Nifty and the BSE SENSEX indexes. Throughout this paper, stock market returns are defined as continuously compounded or log returns (hereafter returns) at time  $t$ ,  $R_t$ , calculated as follows:

$$R_t = \log (P_t / P_{t-1}) = \log P_t - \log P_{t-1} \quad (7)$$

where  $P_t$  and  $P_{t-1}$  are the daily closing values of the NSE S&P CNX Nifty and the BSE SENSEX indexes at days  $t$  and  $t-1$ , respectively.

## EMPIRICAL RESULTS AND DISCUSSION

Table 1 reports the descriptive statistics for the NSE-Nifty and BSE-Sensex returns for the entire study period as well as the return for each day of the week.

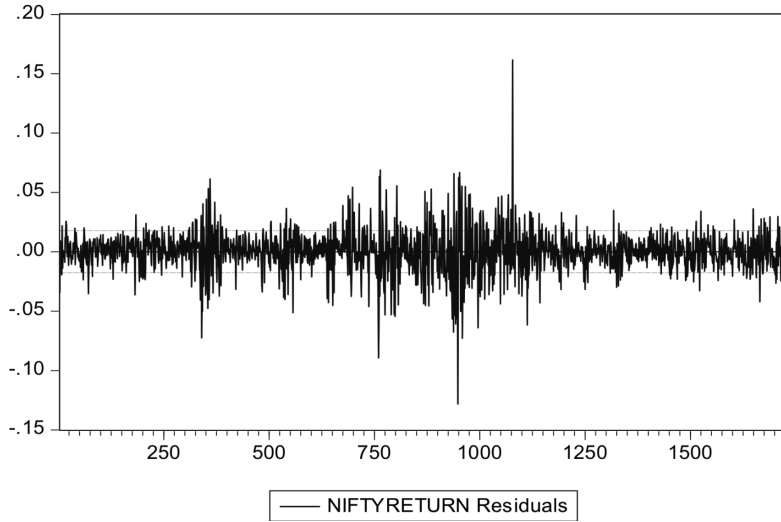
**Table 1** Descriptive statistics

<b>S&amp;P CNX NIFTY Return</b>						
	<b>Monday</b>	<b>Tuesday</b>	<b>Wednesday</b>	<b>Thursday</b>	<b>Friday</b>	<b>Overall</b>
Mean	0.2005	0.2011	0.2017	0.1982	0.1986	0.00045
Std. Dev.	0.4005	0.4009	0.4014	0.3978	0.3988	0.0176
Skewness	1.4954	1.4909	1.4865	1.5136	1.5117	-0.0044
Kurtosis	3.2364	3.2230	3.2097	3.2910	3.2461	10.424
Jarque-Bera	648.88*	644.57*	640.31*	666.68*	652.17*	3973.4*
<b>SENSEX (BSE-30) Return</b>						
	<b>Monday</b>	<b>Tuesday</b>	<b>Wednesday</b>	<b>Thursday</b>	<b>Friday</b>	<b>Overall</b>
Mean	0.1998	0.2010	0.2022	0.1981	0.1987	0.00048
Std. Dev.	0.4000	0.4008	0.4017	0.3987	0.3991	0.0177
Skewness	1.5009	1.4918	1.4829	1.5145	1.5099	0.1075
Kurtosis	3.2527	3.2256	3.1990	3.2938	3.2800	9.5340
Jarque-Bera	652.62*	643.92*	635.42*	666.08*	661.54*	3073.6*

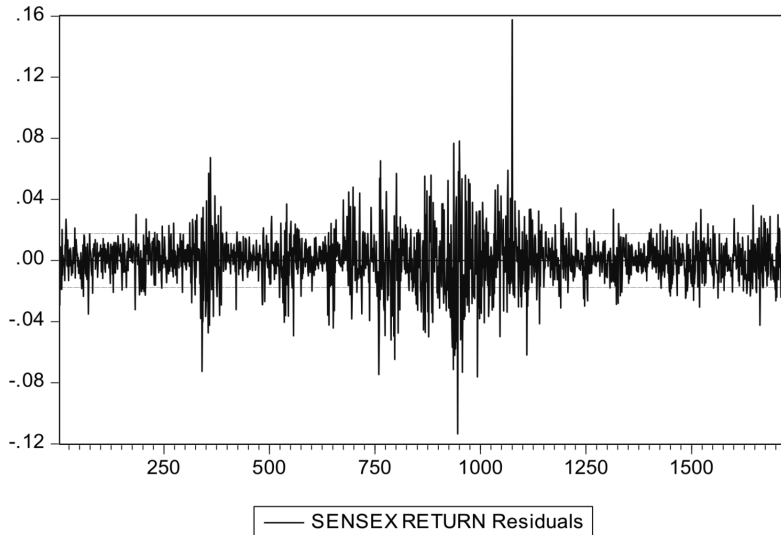
Notes: \*- denote the significance at one level.

From the table result, it is apparent that the maximum average return is on Wednesdays, followed by Tuesdays and Mondays in the case of NSE-Nifty and BSE-Sensex indexes. The mean returns of NSE-Nifty and BSE-Sensex seem to be lowest on Fridays and Thursdays during the study period. This indicates that there were different returns distributions among the days of the week for NSE-Nifty and BSE-Sensex markets, respectively. The standard deviation was highest on Wednesdays, followed by Tuesdays and Mondays in both the markets. The table indicates the fact that the NSE-Nifty and BSE-Sensex indexes were more volatile on Wednesdays and less volatile on Thursdays. It is to be noted that the day traders could gain from such volatility. The values of Skewness and Kurtosis for NSE-Nifty and BSE-Sensex returns as well as those of particular days suggest that the return distributions are not normally distributed. This is further advocated

by the Jarque-Bera test that rejects the null hypothesis of return series is normally distributed at 1% level of significance.



**Figure 1** Graph of residuals series of S&P CNX nifty return



**Figure 2** Graph of residuals series of SENSEX (BSE-30) return

Figures 1 and 2 present the patterns of the residual series of the NSE-Nifty and BSE-Sensex returns for the period under review respectively. The visual inspection indicates the presence of volatility clustering, implying that volatility changes over time and it tends to cluster with periods with low volatility and periods with high volatility in the case of both markets.

**Table 2** Results of Portmanteau Ljung-Box Test and langrange multiplier test

Parameters	S&P CNX Nifty Return	SENSEX (BSE-30) Return
Q[12]	23.832* (0.002)	30.404* (0.002)
Q2[12]	372.25* (0.000)	495.66* (0.000)
ARCH-LM[4]	23.787* (0.000)	25.542* (0.000)

*Notes:* Figures in the parenthesis ( ) indicates p-value. \*- denote the significance at one level. Q[12] and Q<sup>2</sup>[12] represents Portmanteau Ljung-Box (1978) Q-statistics for the return and squared return series respectively. They test for existence of autocorrelation in return and squared return series for 12 lags respectively. Ljung-Box Q test statistic tests the null hypothesis of absence of autocorrelation. ARCH-LM[4] is a Lagrange multiplier test for ARCH effects up to order 4 in the residuals (Engle, 1982).

Besides, Table 2 shows that the Ljung-Box statistics Q(12) and Q<sup>2</sup>(12) for the NSE-Nifty and BSE-Sensex return and squared returns series are highly significant at 1% level respectively. Therefore, we reject the hypothesis that there is no autocorrelation in the level of returns and squared returns. We can observe that the NSE-Nifty and BSE-Sensex return shows evidence of ARCH effects judging from the significant ARCH-LM and Q<sup>2</sup>(12) statistics, which proves the presence of volatility clustering. In other words, the GARCH effect, i.e., time-varying second moment, has been detected in the NSE-Nifty and BSE-Sensex returns series. Thus the use of GARCH-type models for the conditional variance is justified.

**Table 3** Unit root test results

Variables	Augmented Dickey-Fuller Test		
	Intercept	With intercept & trend	Without intercept & trend
NSE-NIFTY	-39.152*	-39.171*	-39.139*
BSE-SENSEX	-38.450*	-38.475*	-38.434*

*Notes:* \* – indicates significance at one per cent level. Optimal lag length is determined by the Schwarz Information Criterion (SIC).

The Augmented Dickey-Fuller (ADF) test was employed to test the stationarity of time-series data considered under the study and the results are presented in Table 3. The unit root test strongly rejects the null hypothesis of non-stationarity for both the NSE-Nifty and BSE-Sensex returns. This indicates the weak-form inefficiency of the Indian stock markets, signifying that there is systematic way to exploit trading opportunities and acquire excess profits. This provides an opportunity to the traders for predicting the future prices and earning abnormal profits.

**Table 4** Results of estimated GARCH Models for S&P CNX NIFTY returns

	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
<b>Mean Equation</b>			
Rt-1	0.069046* (2.591)	0.077035* (2.817)	0.088803* (3.262)
Monday	0.001776** (2.338)	0.001242*** (1.676)	0.001524*** (1.715)
Tuesday	0.000122 (0.200)	-0.000206 (-0.347)	0.000120 (0.213)
Wednesday	0.001547** (1.942)	0.001043*** (1.896)	0.001405** (2.410)
Thursday	0.000903 (1.306)	0.000287 (0.419)	0.000114 (0.189)
Friday	0.001050 (1.394)	0.000560 (0.732)	0.000531 (0.772)
<b>Variance Equation</b>			
$\omega_1$	2.23E-05*** (1.940)	2.64E-05** (2.340)	-0.389396* (-4.420)
$\alpha_1$	0.116930* (9.378)	0.031311* (2.760)	0.233315* (10.474)
$\delta_1$	0.866299* (65.91)	0.862861* (66.64)	0.957675* (161.85)
$\gamma_1$	–	0.161916* (7.053)	-0.130972* (-7.842)
Monday	5.54E-06 (0.332)	1.19E-05 (0.736)	0.174697 (1.611)
Tuesday	-6.76E-05* (-3.538)	-7.77E-05* (-4.171)	-0.628741* (-4.529)
Thursday	-1.35E-05 (-0.739)	-1.83E-05 (-1.036)	-0.200342 (-1.641)

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Table 4 (Cont'd)

Friday	-6.93E-06 (-0.414)	-1.04E-05 (-0.648)	-0.098912 (-0.848)
Q2[12]	9.0389 (0.755)	7.585 (0.817)	10.147 (0.603)
ARCH-LM[4]	0.334 (0.563)	1.321 (0.250)	1.779 (0.182)

Notes: Figures in parenthesis are z-statistics, \*, \*\* and \*\*\*- denotes the significance at one, five and ten percent level, respectively. Q2(12) represents the Ljung-Box Q-statistics for the model squared standardized residuals using 12 lags. ARCH-LM[4] is a Lagrange multiplier test for ARCH effects up to order 4 in the residuals (Engle, 1982).

The estimation results of the symmetric and asymmetric GARCH-type models for NSE-Nifty market returns can be found in Table 4. The empirical findings of GARCH (1,1) model reveal a positive Monday and Wednesday effects exist in the NSE-Nifty market returns at 5% levels. The average return on Monday is significantly higher than the average return of Wednesday in the NSE-Nifty market. In addition, results derived from the EGARCH (1,1) and TGARCH (1,1) models are consistent with the results of GARCH (1,1) model that positive Monday and Wednesday effects are still persist in the NSE-Nifty Index returns. The table result reveals that the ARCH and GARCH terms in conditional variance equations are positive and significant at 1% level in all GARCH estimations, implying a strong support for the ARCH and GARCH effects. Moreover, the estimated asymmetric coefficients of EGARCH (1,1) and TGARCH (1,1) model show that the NSE-Nifty Index returns exhibit statistically significant asymmetric (leverage) effects at 1% level respectively. Most importantly, the empirical results indicate that estimated coefficients of Tuesday in the conditional variance equations are negative and statistically significant at 1% levels. This implies that Tuesdays has negative impact on volatility after controlling the persistence and asymmetric effects. In Table 4, ARCH-LM test and Ljung-Box Q-statistics does not indicates the presence of a significant ARCH effect in the residual series which means that the conditional variance equations of the GARCH-type models are well specified.

**Table 5** Results of Estimated GARCH Models for SENSEX (BSE-30) return

	<b>GARCH (1,1)</b>	<b>TGARCH (1,1)</b>	<b>EGARCH (1,1)</b>
<b>Mean Equation</b>			
Rt-1	0.079829* (3.043)	0.088369* (3.276)	0.088188* (3.270)
Monday	0.001829** (2.455)	0.001228*** (1.693)	0.001508*** (1.873)
Tuesday	0.000118 (0.193)	-0.000133 (-0.225)	-7.78E-05 (-0.132)
Wednesday	0.001547** (2.276)	0.001171*** (1.714)	0.001475* (2.594)
Thursday	0.000860 (1.239)	0.000267 (0.389)	1.26E-05 (0.021)
Friday	0.001068 (1.449)	0.000554 (0.738)	0.000523 (0.760)
<b>Variance Equation</b>			
$\omega_1$	2.12E-05*** (1.940)	2.28E-05** (2.163)	-0.320864* (-3.659)
$\alpha_1$	0.114020* (8.817)	0.036044* (3.506)	0.225235* (10.394)
$\delta_1$	0.869885* (62.77)	0.868731* (66.01)	0.963074* (172.30)
$\gamma_1$	–	0.147587* (6.549)	-0.112986* (-7.276)
Monday	3.05E-06 (0.188)	1.02E-05 (0.648)	0.121442 (1.093)
Tuesday	-6.55E-05* (-3.582)	-7.21E-05* (-4.050)	-0.633790* (-4.541)
Thursday	-1.34E-05 (-0.778)	-1.57E-05 (-0.958)	-0.267314 (-1.476)
Friday	-3.50E-06 (-0.219)	-4.56E-06 (-0.299)	-0.055823 (-0.486)
Q2[12]	11.343 (0.581)	14.133 (0.292)	14.043 (0.298)
ARCH-LM[4]	0.834 (0.360)	2.648 (0.103)	1.583 (0.271)

*Notes:* Figures in parenthesis are z-statistics, \*, \*\* and \*\*\*- denotes the significance at one, five and ten percent level, respectively. Q2(12) represents the Ljung-Box Q-statistics for the model squared standardized residuals using 12 lags. ARCH-LM[4] is a Lagrange multiplier test for ARCH effects up to order 4 in the residuals (Engle, 1982).

Table 5 provides the estimation results of the symmetric and asymmetric GARCH-type models for BSE-SENSEX market returns. The empirical evidence of GARCH (1,1) model reveal a positive Monday and Wednesday effects exist in the BSE-SENSEX market returns at 5% levels. The average return on Monday is significantly higher than the average return of Wednesday in the BSE-SENSEX market. Further, the results derived from the EGARCH (1,1) and TGARCH (1,1) models show that positive Monday and Wednesday effects are still persist in the BSE-SENSEX market returns. The empirical evidences of the GARCH-type models indicate significant ARCH and GARCH effects. Moreover, the EGARCH (1,1) and TGARCH (1,1) models show that the BSE-SENSEX market returns exhibit statistically significant asymmetric (leverage) effects at 1% level respectively. The day-of-the-week effects on conditional variance imply that Tuesday effect is negative and statistically significant at 1% level in all GARCH type models. Finally, the ARCH-LM test and Ljung-Box Q-statistics does not indicates the presence of a significant ARCH effect in the residual series which means that the conditional variance equations of the GARCH-type models are well specified.

## CONCLUSION

This paper investigates empirically the day-of-the-week effect on stock returns and volatility of the Indian stock markets. The GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models were employed to examine the existence of daily anomalies over the period of 1<sup>st</sup> July, 1997 to 29<sup>th</sup> June, 2012. The empirical results derived from the GARCH models indicate the existence of day-of-the-week effects on stock returns and volatility of the Indian stock markets. The study reveals positive Monday and Wednesday effects in the NSE-Nifty and BSE-SENSEX market returns. The average return on Monday is significantly higher than the average return of Wednesday in the NSE-Nifty and BSE-SENSEX markets. Besides, the findings confirm the strong support of ARCH and GARCH effects persist in the returns series. Moreover, the asymmetric GARCH models show that the Indian stock market returns exhibit asymmetric (leverage) effect. Most importantly, the empirical results indicate that Tuesday effects have negative impact on volatility after controlling the persistence and asymmetric effects. As a result of the existence of day-of-the-week effects, the study suggests that the Indian stock markets are weak-form inefficient. This signifies that there exists an opportunity to the traders for predicting the future prices and earning abnormal profits in the Indian stock markets through day-of-the-week anomalies.



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