Capturing the month of the year effect in the Indian stock market using GARCH models

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Abstract

Purpose – In the research of stock market efficiency, it is argued that the stock market moves randomly and absorbs all the available information. As a result, it is quite impossible to make predictions about the possible future movement by the investors. But literatures have detected certain calendar anomalies where a day(s) in a week or month(s) in a year or a particular event in a year becomes conducive for investors to earn more than the normal. Hence, the purpose of this study is to find out the month of the year effect in the Indian stock market.

Design/methodology/approach – In this study, daily time series data of Sensex and Nifty from 1996 to 2021 is used. The study uses month dummies to capture the effect. Different variants of generalised autoregressive conditional heteroskedasticity (GARCH) models, both symmetric and asymmetric, are used in the study to model the conditional volatility in the presence month effect.

Findings – This study found the September effect in the return series of both the stock market. Apart from that, asymmetric GARCH models are found to be the best fit model to estimate conditional volatility.

Originality/value – This study is an endeavour to study month of the year effect in the Indian context. This research will provide valuable insight for studying the different calendar anomalies.

Keywords Stock market, Return, Volatility, Month of the year effect, GARCH, Calendar anomalies

Paper type Research paper

1. Introduction

Studying the behaviour of the stock market is one of the complex subjects in the field of finance. Different people observe, think differently and act accordingly. Researchers have carried out studies from different contexts to capture the behaviour of the stock market. Return and volatility are two interrelated and inherent parts of the stock market behaviour. The

efficient market theory is one of the pillars of portfolio management. Developing the Efficient Market Hypothesis, Fama (1965, 1970) laid the foundation stone for further research in understanding the stock market behaviour. It proposes that share price does not follow any pattern means random which reduces the chance to earn an abnormal return. But a number of studies have documented the presence of different patterns in return and volatility. Investors use these approaches to generate more than the normal return from the market. One such pattern is calendar effects. This calendar effect includes the day of the week effect, the month of the year effect, January effect, daylight savings effect, holiday effect, turn of the month effect, etc. This paper is an attempt in investigating the existence of the month of the year effect using generalised autoregressive conditional heteroskedasticity (GARCH) models.

2. Review of literature

The research evidence on the influence of the month of the year effect is relatively less observed comparing to the day effect as far as the emerging markets like India are concerned. The month of the year effect is a pattern in the returns of the financial assets where the return of a particular month of a year is significantly higher comparing to other months. This effect is documented in several studies in the world. One of the earlier studies by Berges et al. (1984) reported the higher average return in the month of January comparing to other months. Ignatius (1992) also found this effect in the case of India as well as US markets. The average return of December emerges as the highest return generating month. Analysing the return data of nine developed and emerging countries, Boudreaux (1995) also documented the presence of month of the year effect. Using a non-linear GARCH model in the Germany, US and UK stock markets, Choudhary (2001) found the January effect as well as the month of the year effect. Later on, the study of Parikh (2008) found a December effect in the Indian Stock market. His study supports the earlier study of Ignatius (1992). The study of Chaouachi and Douagi (2014) was on the Tunisian stock market from 1998 to 2011. The study found the presence of this effect. The study revealed the significant effect of January, March, April, August and September on the Tunisian stock market. Similarly, Ciccone and Etebari (2008) also captured the January and September effect in four international markets such as France, UK, Japan and Germany out of five considered for the study. Kaur (2004) studied this effect in the Indian context using the symmetric as well as asymmetric GARCH models to estimate the conditional volatility by capturing the month of the year effect and found the presence of the same effect and reported that the GARCH models that are asymmetric outperform symmetric. However, Floros (2008) reported the significance of June and October in the Greece stock market. Analysing for the period 1980–2009, Ke et al. (2014) found the February effect in the Taiwan stock exchange. Similarly, Munir and Ching (2018) disclosed the presence of month effect on the share value of the selected banking and non-banking companies in Malaysia. In a recent study by Bajaj et al. (2019), September effect was detected in Indian stock market.

The above discussed studies have used proper econometric methods in the estimation of the month effect. But some other studies are also there which uses only descriptive statistics or some simple estimation tools such as t-test, analysis of variance (ANOVA) to explain this behaviour of the stock market. The study of Verma and Vijay Kumar (2008) is one of them where they have used the descriptive statistics, ANOVA and regression analysis in Bombay stock exchange. The mean returns of the months are found to be positive except the month of October. The regression result finds the insignificance of the month coefficients which indicate the disappearance of month effect in the Bombay stock market. Similarly, Mehta and Chander (2009) studied by using the same techniques like descriptive statistics, Kruskal–Wallis H test and regression analysis revealed that November and December

months can be considered to be important for investors to attain abnormal returns. Another study on the Ukrainian stock market by Caporale and Plastun (2017) discovered that while calendar irregularities are not evident in the spot market, they are present in the future market. After reviewing the above literatures, one thing is found that there are more or less certain trends or patterns in the stock markets across the world that affects the return generating process of the investors. But the lesser focus is on the world's fastest expanding economy, India. Another thing is the short study period that covers five to ten years. Hence, this study takes into account 25 years of data to analyse and generalise this phenomenon of the Indian stock market.

3. Data and methodology
The analysis was carried out with the time-series data of the index values collected from two active Indian stock exchanges. They are the Bombay stock exchange and the National stock exchange. The daily Sensex and Nifty values from 1996 to 2021 were collected and further processed to find out the return for the purpose of the analysis. A total of 6,203 and 6,223 observations in the case of Sensex and Nifty, respectively, were used in this study. The difference in the total number of observations is primarily attributable to the trading halt, may be due to the activation of circuit breaker, in a trading day or trading holidays declared in the stock exchanges. The main intention of the current research is to estimate the conditional volatility by capturing the month of the year effect. For this purpose, GARCH, exponential generalised autoregressive conditional heteroskedasticity (EGARCH), threshold generalised autoregressive conditional heteroskedasticity (TGARCH) and power generalised autoregressive conditional heteroskedasticity (PGARCH) models are used. The autoregressive conditional heteroskedasticity (ARCH) and GARCH terms used in the equations are of order one. GARCH (1,1) model is the basic model that explains the conditional variance in the time series. Tim Bollerslev (1986) introduced this concept in, which is an expansion of Engel's ARCH model. This model is based on the premise that today's conditional variance is influenced by past conditional variance. The GARCH models conveniently account for the clustering of the volatility in the time series data of any financial assets. But the basic GARCH model has a major limitation because of the fact that it is symmetric. It means that the signs of the error term are ignored as this term is squared in the variance equation. However, the financial market exhibits positive and negative shocks. To capture these shocks in the time series data, Nelson (1991), Glosten *et al.* (1993), Zakoi±an (1994) and Ding *et al.*(1993) introduced certain extensions to the basic model. They are TGARCH, EGARCH and PGARCH models. The mean equation and variance equation of different GARCH models are as follows.

3.1 GARCH model

$$R_t = \delta_1 M_1 + \delta_2 M_2 + \delta_3 M_3 + \delta_4 M_4 + \ldots\ldots\ldots + \delta_{12} M_{12} + R_{t-1} + u_t \qquad [1]$$

$$u_t \mid I_{t-1} N(0, h_t)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad [2]$$

where R_t is the return of Sensex and Nifty returns which is considered to be linearly related to the month dummy variables and past return. M_1 to M_{12} are the months starting from January to December. In equation (2), h_t is the conditional variance. Thus equation (1) is the

mean equation, whereas equation (2) is the variance equation. In the variance equation, α_i is the ARCH coefficient and β_j is the GARCH coefficient.

3.2 EGARCH model

$$\log(h_t) = \omega + \sum_{j=1}^{q} \alpha_j | \frac{u_{t-j}}{\sqrt{h_{t-j}}} | + \sum_{j=1}^{q} \gamma_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \beta_i \log(h_{t-i})$$ [3]

Here, the conditional variance of the return is expressed in logarithmic form, resulting in an exponential rather than quadratic leverage effect. As a consequence, the conditional variance would be greater than zero. Here, γ_j is the leverage parameter and if $\gamma_1 = \gamma_2 = \ldots\ldots.. = 0$, then the model is asymmetric. When $\gamma_j < 0$, then it can be said that the volatility because of positive news is lower than that of bad news.

3.3 TGARCH model

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \gamma_i u_{t-i}^2 d_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j}$$ [4]

Here a dummy variable "d_t" is used in equation [4] which takes the value of 1 in the case when $u_t < 0$, otherwise it is 0. Thus, in TGARCH model, the impact of good news is captured by the γ_i coefficient, whereas the impact of the bad news can be captured by adding the coefficients of the residual term with the coefficient of the multiplicative dummy variable. If the value of the coefficient γ_i, is greater than 0, then it indicates the dominant role of bad news in increasing the volatility.

3.4 PGARCH model

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i(|u_{t-i}| - \gamma_i u_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta$$ [5]

where $\delta > 0, |\gamma| < = 1$ for $i = 1, 2, \ldots\ldots..,r, i = 0$ for all $i > $r, and r $\leq p$. All i are set to 0 in this symmetric model. A PGARCH model is just a regular GARCH specification if $\delta = 2$ and $i = 0$ for every i. If the value of γ is less than 1, the asymmetric effect is evident. In the current study, δ is kept as 1 so that standard deviation or volatility can be directly calculated.

4. Empirical results

The results indicated the presence of month effects in the return series of these stock exchanges. The descriptive statistics of Sensex and Nifty returns are displayed in Tables 1 and 2. This includes the mean, median, standard deviation, skewness, kurtosis and Jarque–Bera test statistics along with the probability values. It can be observed from the table that, the mean returns of the selected index were positive except March and October. The highest return was in the month of December. Similarly, the standard deviation in both the markets was highest in the month of March and May followed by October. Kurtosis suggests that the index data is leptokurtic. The result of Jarque–Bera statistics rejects the normality assumption about the index data series.

The unit root test outcomes are displayed in Table 3. Both the tests confirmed that there is no presence of unit root. Table 4 shows the results of the estimated mean equation as well as variance equation [i.e. equations (1) and (2)]. The coefficients of the mean equation in the case of

Particulars	January	February	March	April	May	June	July	August	September	October	November	December
Mean	0.000139	0.000362	-0.000201	0.001317	0.000337	0.000818	0.000741	0.000213	0.000399	-8.37E-05	0.000955	0.001597
Median	0.000316	0.000358	0.000599	0.001401	0.000753	0.001153	0.000900	0.000718	0.000958	0.000553	0.001173	0.001258
Maximum	0.073772	0.065358	0.069796	0.089749	0.173393	0.075882	0.059421	0.036872	0.054577	0.082210	0.057392	0.055138
Minimum	-0.074070	-0.051163	-0.131526	-0.071539	-0.111385	-0.058090	-0.061680	-0.059362	-0.058494	-0.109564	-0.066103	-0.038415
Std. dev.	0.014946	0.013978	0.018777	0.016593	0.018168	0.014462	0.013896	0.012373	0.014022	0.016963	0.013445	0.011989
Skewness	0.018591	0.101748	-1.033878	0.074483	1.124309	0.114485	-0.136260	-0.394903	-0.278879	-0.468745	0.055261	0.294615
Kurtosis	7.358958	5.438205	10.14413	7.306303	22.16050	6.186982	5.876320	4.698271	5.339754	9.579450	6.334652	5.116887
Jarque–Bera	418.8334	123.4665	1184.645	370.5552	8203.489	227.1566	192.3399	76.29719	123.9071	933.0502	233.3107	105.4201
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	529	495	514	479	529	534	553	522	514	507	503	524

Table 1.
Descriptive statistics for Sensex returns

Particulars	January	February	March	April	May	June	July	August	September	October	November	December
Mean	5.26E-05	0.000291	1.20E-05	0.001150	0.000316	0.000720	0.000692	0.000227	0.000496	−0.000108	0.001020	0.001711
Median	0.000127	0.000739	0.000824	0.001474	0.000282	0.001186	0.000637	0.000731	0.000722	0.000126	0.001482	0.001633
Maximum	0.075484	0.055290	0.104441	0.087632	0.177441	0.072959	0.055824	0.037055	0.053191	0.072051	0.058947	0.051814
Minimum	−0.087024	−0.051432	−0.129805	−0.074202	−0.122377	−0.055965	−0.058439	−0.059151	−0.053514	−0.122029	−0.066577	−0.044761
Std. dev.	0.015248	0.013414	0.018806	0.016559	0.018129	0.014348	0.013360	0.012225	0.013731	0.017382	0.013306	0.012033
Skewness	0.056344	−0.118031	−0.770155	0.164006	1.016158	0.056605	−0.128216	−0.391284	−0.287036	−0.677482	−0.007898	0.183563
Kurtosis	7.893254	4.741195	11.26614	7.795059	24.93767	5.636352	5.502381	4.894473	5.147910	10.80566	6.389092	4.730877
Jarque–Bera	529.0424	63.67934	1520.084	464.8911	10799.96	154.9305	145.2727	91.90653	106.4821	1328.508	242.1673	68.61484
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	530	495	516	483	534	534	551	525	517	508	506	526

Table 2.
Descriptive statistics
for Nifty returns

Sensex and Nifty are found to be positive in all the months. As far as the statistical significance is concerned, Sensex shows the significance of February, May, June, September, October, November and December. Similarly, Nifty shows the significance of March, May, September, October, November and December. All these months are statistically significant at 5%. ARCH and GARCH coefficients are so significant and the sum of the coefficients is less than one in the case of Sensex and Nifty. Thus, the conditional volatility seems to be a little bit explosive in nature, meaning that the volatility has increased gradually over the time in an exponential manner. The large GARCH coefficient indicates its persistence. All the months have been found to have a positive effect on both the return series. The diagnostic tests such as Ljung Box Q statistics represents the squared residuals did not show the presence of autocorrelation and in the same way, autoregressive conditional heteroskedasticity (ARCH) LM test shows the absence of the ARCH effect.

The estimated results of equation (3) are shown in Table 5. It is evident that there is the presence of asymmetries in both the stock markets while capturing the month of the year effect. Interestingly, Sensex and Nifty show the September effect. Apart from the above mentioned months, the Nifty return series shows some different effects. Here, April in case of Bombay Stock Exchange and March in the case of National Stock Exchange shows significance. Looking at the variance equation, it is found that there is the presence of leverage effect in both the return series. The leverage parameter is negative and significant in both cases. The negative leverage term shows that bad news plays a greater role in increasing the volatility more comparing the good news of a similar scale would do while capturing the month of the year effect. The significance of conditional volatility is also observed. Both are significant at 1%. Here, the GARCH coefficient in the above estimation is covariance stationary as $\sum_{i=1}^{p} \beta_i < 1$ (Zivot, 2008). The diagnostic tests suggest the absence of autocorrelation and ARCH effect in the residuals.

Similarly, Table 6 displays the estimated results of the TGARCH equation. This also indicated some asymmetric evidence while capturing the month of the year effect in the return series. Like the EGARCH model, the study exhibits the September effect which is significant statistically at a 5% level. Interestingly, May and December also show their significance in both the return series. All the parameters in the conditional variance equation are found to be statistically significant in the presence of the month of the year effect. The diagnostic tests suggest that there is no presence of autocorrelation and ARCH effect in the residuals.

As indicated in Table 7, PGARCH results reveal the presence of asymmetries. Both indices' return series show that September has a considerable effect and, additionally, Nifty also captured the December effect. March in the case of Nifty and April in the case of Sensex are found to be significant. ARCH and GARCH coefficients are statistically significant including the asymmetry coefficient. Like in all other estimations, the diagnostic tests suggest that there is no presence of autocorrelation and ARCH effect in the residuals.

	Sensex		Nifty	
Parameters	ADF test	PP test	ADF test	PP test
Level	−74.6741 (0.0001)***	−74.6702 (0.0001)***	−75.2369 (0.0001)***	−75.2553 (0.0001)***
Intercept	−74.7607 (0.0001)***	−74.7236 (0.0001)***	−75.3263 (0.0001)***	−75.3059 (0.0001)***
Trend and intercept	−74.7552 (0.0001)***	−74.7178 (0.0001)***	−75.3206 (0.0001)***	−75.30002 (0.0001)***

Notes: ADF: Augmented Dickey–Fuller test, PP: Phillip–Perron test. *, ** and *** indicate statistically significant at 10%, 5% and 1%, respectively

Table 3.
Results of unit root test of daily returns

	Sensex				Nifty		
Variables	Coefficient	Std. error	z-statistic	Variables	Coefficient	Std. error	z-statistic
JANUARY	0.000575	0.000404	1.421898	JANUARY	0.000554	0.000418	1.325730
FEBRUARY	0.000510	0.000438	1.164593	FEBRUARY	0.000214	0.000445	0.480779
MARCH	0.000971	0.000527	1.844662*	MARCH	0.001225	0.000517	2.367222**
APRIL	0.000736	0.000501	1.469235	APRIL	0.000663	0.000501	1.322344
MAY	0.001092	0.000441	2.475568**	MAY	0.001051	0.000438	2.399501**
JUNE	0.001073	0.000507	2.118158**	JUNE	0.000948	0.000514	1.845342
JULY	0.000821	0.000435	1.888864*	JULY	0.000818	0.000425	1.923102*
AUGUST	0.000454	0.000435	1.043088	AUGUST	0.000526	0.000442	1.189467
SEPTEMBER	0.000888	0.000385	2.306410**	SEPTEMBER	0.000799	0.000383	2.086787**
OCTOBER	0.000991	0.000482	2.054911**	OCTOBER	0.001052	0.000519	2.025627**
NOVEMBER	0.001289	0.000513	2.515445**	NOVEMBER	0.001292	0.000519	2.489319**
DECEMBER	0.000964	0.000416	2.317567**	DECEMBER	0.001029	0.000417	2.466620**
Return(−1)	0.072445	0.013768	5.261952***	Return(−1)	0.070617	0.013655	5.171484***
Variance equation				Variance equation			
ω	2.42E-06	2.97E-07	8.135466***	ω	2.63E-06	2.93E-07	8.975182***
α	0.105572	0.005104	20.68356***	α	0.109913	0.005107	21.52169***
β	0.888120	0.004946	179.5461***	β	0.884138	0.004878	181.2368***
Log likelihood	18325.00	Akaike info criterion	−5.904224	Log likelihood	18329.90	Akaike info criterion	−5.890608
Durbin–Watson stat	2.0362	Schwarz criterion	−5.886855	Durbin–Watson stat	2.044249	Schwarz info criterion	−5.873277
Diagnostic tests							
Ljung Box Q (1)	0.0870 (0.786)	ARCH LM Test (1)		Ljung Box Q (1)	0.1627 (0.6870)	ARCH LM Test (1)	0.1625 (0.6868)
Ljung Box Q (5)	4.2485 (0.541)	ARCH LM Test (5)		Ljung Box Q (5)	3.7780 (0.582)	ARCH LM Test (5)	0.7627 (0.5766)

Notes: Ljung Box Q statistics represents the squared residuals up to lag 5. *, ** and *** indicate statistically significant at 10%, 5% and 1%, respectively

Table 4.
GARCH (1, 1)
estimates for the
month-of-the-year
effect

Table 5.
EGARCH (1, 1) estimates for the month-of-the-year effect

Variables	Sensex Coefficient	Std. error	z-statistic	Variables	Nifty Coefficient	Std. error	z-statistic
JANUARY	0.000413	0.000362	1.140761	JANUARY	0.000419	0.000374	1.122418
FEBRUARY	0.000482	0.000410	1.176101	FEBRUARY	9.00E-05	0.000451	0.199487
MARCH	0.000648	0.000432	1.501440	MARCH	0.000841	0.000420	2.001470**
APRIL	0.000763	0.000438	1.741558*	APRIL	0.000374	0.000441	0.848831
MAY	0.000435	0.000393	1.106278	MAY	0.000372	0.000377	0.985320
JUNE	0.000437	0.000455	0.960568	JUNE	0.000269	0.000452	0.594926
JULY	0.000353	0.000435	0.812756	JULY	0.000395	0.000425	0.930145
AUGUST	0.000101	0.000403	0.250501	AUGUST	0.000134	0.000394	0.339447
SEPTEMBER	0.001013	0.000356	2.843531***	SEPTEMBER	0.001310	0.000343	3.818945***
OCTOBER	0.000193	0.000411	0.469915	OCTOBER	0.000137	0.000431	0.318664
NOVEMBER	0.000495	0.000471	1.049767	NOVEMBER	0.000560	0.000471	1.189118
DECEMBER	0.000491	0.000407	1.207097	DECEMBER	0.000667	0.000374	1.783278*
Return(−1)	0.083486	0.013011	6.416321***	Return(−1)	0.083629	0.012881	6.492271***
Variance equation				Variance equation			
ω	−0.354190	0.021404	−16.54793***	ω	−0.356018	0.019710	−18.06323***
α	0.211970	0.008937	23.71850***	α	0.211165	0.008246	25.60926***
γ	−0.077388	0.005327	−14.52741***	γ	−0.084537	0.005536	−15.27166***
β	0.978001	0.002030	481.8220***	β	0.977582	0.001939	504.1380***
Log likelihood	18376.96	Akaike info criterion	−5.920659	Log likelihood	18388.42	Akaike info criterion	−5.909108
Durbin–Watson stat	2.058669	Schwarz info criterion	−5.902205	Durbin–Watson stat	2.070174	Schwarz info criterion	−5.890694
Diagnostic tests							
Ljung Box Q (1)	0.0369 (0.848)	ARCH LM Test (1)	0.0368 (0.8478)	Ljung Box Q (1)	0.0048 (0.9450)	ARCH LM Test (1)	0.0047 (0.9450)
Ljung Box Q (5)	3.3249 (0.650)	ARCH LM Test (5)	0.6599 (0.6539)	Ljung Box Q (5)	2.8156 (0.7280)	ARCH LM Test (5)	0.5623 (0.7290)

Notes: Ljung Box Q statistics represents the squared residuals up to lag 5. *, ** and *** indicate statistically significant at 10%, 5% and 1%, respectively

Table 6. TGARCH (1,1) estimates for the month-of-the-year effect

Variables	Sensex			Variables	Nifty		
	Coefficient	Std. error	z-statistic		Coefficient	Std. error	z-statistic
JANUARY	0.000381	0.000382	0.996326	JANUARY	0.000386	0.000396	0.974574
FEBRUARY	0.000454	0.000412	1.101894	FEBRUARY	0.000215	0.000443	0.486343
MARCH	0.000607	0.000498	1.218696	MARCH	0.000819	0.000496	1.650731*
APRIL	0.000476	0.000494	0.964352	APRIL	0.000317	0.000493	0.642286
MAY	0.000726	0.000419	1.733046*	MAY	0.000716	0.000408	1.756068*
JUNE	0.000633	0.000466	1.357539	JUNE	0.000440	0.000478	0.920844
JULY	0.000415	0.000450	0.922295	JULY	0.000399	0.000427	0.934132
AUGUST	0.000228	0.000414	0.551941	AUGUST	0.000234	0.000423	0.552641
SEPTEMBER	0.000889	0.000376	2.365340**	SEPTEMBER	0.000856	0.000388	2.207538**
OCTOBER	0.000384	0.000431	0.891573	OCTOBER	0.000445	0.000440	1.012002
NOVEMBER	0.000824	0.000491	1.677373	NOVEMBER	0.000810	0.000496	1.634675
DECEMBER	0.000750	0.000422	1.777988*	DECEMBER	0.000804	0.000415	1.937202*
Return (−1)	0.081960	0.013764	5.954527***	Return (−1)	0.080397	0.013577	5.921720***
Variance equation				*Variance equation*			
ω	2.92E-06	3.01E-07	9.712202***	ω	3.07E-06	3.00E-07	10.24100***
α	0.055136	0.004887	11.28225***	α	0.055587	0.005365	10.36127***
γ	0.104137	0.008592	12.12095***	γ	0.110933	0.008708	12.73971***
β	0.883374	0.005371	164.4600***	β	0.880520	0.005242	167.9835***
Log likelihood	18369.34	Akaike info criterion	−5.918202	Log likelihood	18375.38	Akaike info criterion	−5.904914
Durbin–Watson stat	2.056186	Schwarz info criterion	−5.899747	Durbin–Watson stat	2.06463	Schwarz info criterion	−5.886500
Diagnostic tests							
Ljung Box Q (1)	0.4474	ARCH LM Test (1)	0.4469	Ljung Box Q (1)	0.5927	ARCH LM Test (1)	0.5921
	(0.5040)		(0.5038)		(0.4410)		(0.4416)
Ljung Box Q (5)	1.3889	ARCH LM Test (5)	0.2728	Ljung Box Q (5)	1.8662	ARCH LM Test (5)	0.3645
	(0.9260)		(0.9281)		(0.867)		(0.8730)

Notes: Ljung Box Q statistics represents the squared residuals up to lag 5. *, ** and *** indicate statistically significant at 10%, 5% and 1%, respectively

Table 7. PGARCH (1,1) estimates for the month-of-the-year effect

	Sensex				Nifty		
Variables	Coefficient	Std. error	z-statistic	Variables	Coefficient	Std. error	z-statistic
JANUARY	0.000415	0.000360	1.151469	JANUARY	0.000441	0.000370	1.194370
FEBRUARY	0.000566	0.000403	1.405403	FEBRUARY	0.000144	0.000441	0.327395
MARCH	0.000644	0.000436	1.475496	MARCH	0.000855	0.000424	2.015424**
APRIL	0.000739	0.000446	1.658619*	APRIL	0.000317	0.000448	0.707521
MAY	0.000378	0.000390	0.968337	MAY	0.000301	0.000373	0.806159
JUNE	0.000407	0.000456	0.892658	JUNE	0.000253	0.000446	0.566855
JULY	0.000309	0.000440	0.702205	JULY	0.000338	0.000422	0.800828
AUGUST	2.58E-05	0.000405	0.063731	AUGUST	6.27E-05	0.000395	0.158814
SEPTEMBER	0.001173	0.000354	3.314565***	SEPTEMBER	0.001480	0.000321	4.608167***
OCTOBER	0.000170	0.000397	0.427480	OCTOBER	8.35E-05	0.000411	0.203000
NOVEMBER	0.000464	0.000473	0.982234	NOVEMBER	0.000510	0.000467	1.091593
DECEMBER	0.000501	0.000406	1.232209	DECEMBER	0.000869	0.000346	2.510884**
Return (−1)	0.083605	0.012734	6.565589***	Return (−1)	0.090474	0.012505	7.234884***
Variance equation				*Variance equation*			
ω	0.000283	2.67E-05	10.59194***	ω	0.000287	2.54E-05	11.29126***
α	0.114525	0.004936	23.20443***	α	0.115463	0.004409	26.18664***
γ	0.391117	0.028511	13.71801***	γ	0.430370	0.029535	14.57173***
β	0.892000	0.004890	182.4040***	β	0.891905	0.004185	213.1007***
Log likelihood	18370.90	Akaike info criterion	−5.918379	Log likelihood	18380.53	Akaike info criterion	−5.906570
Durbin–Watson stat	2.058676	Schwarz info criterion	−5.898839	Durbin–Watson stat	2.083268	Schwarz info criterion	−5.888156
Diagnostic tests							
Ljung Box Q (1)	0.4147	ARCH LM Test (1)	0.4142	Ljung Box Q (1)	0.3084	ARCH LM Test (1)	0.3080
	(0.520)		(0.5198)		(0.5790)		(0.5789)
Ljung Box Q (5)	5.2240	ARCH LM Test (5)	1.0223	Ljung Box Q (5)	4.7911	ARCH LM Test (5)	0.9502
	(0.3890)		(0.4025)		(0.4420)		(0.4471)

Notes: Ljung Box Q statistics represents the squared residuals up to lag 5. *, ** and *** indicate statistically significant at 10%, 5% and 1%, respectively

5. Discussion and conclusion

In this article, an attempt was made to capture the month effect in the Indian stock market and further to estimate the conditional variance or volatility. By using both forms of the GARCH models, i.e. symmetric and asymmetric, it is found the presence of the above effects in the returns and volatility. The nature of the month of the year effect seems to be a little different across months. Both the series shows the same months to influence the return series except June in the case of Sensex return while March in the case of the Nifty series. This study did not find the presence of January effect as was detected by Berges *et al.* (1984), Ignatius (1992) and Choudhary (2001). However, the study detected the September effect consistently throughout the study period in all the estimations of return series. This present study supports the study of Ciccone and Etebari (2008), Ke *et al.* (2014) and Bajaj *et al.* (2019). The September effect as detected in the study has several plausible explanations. For Indians, the festive season begins in September. This season provides a significant stimulus to India's economy resulting in a favourable effect on the stock market. The quarterly results of the first quarter come in August which has also a certain effect on the stock market. A good monsoon has an impact on the stock market performance as well. Seasonal psychological bias has a beneficial effect on the market. The study's findings revealed the presence of the leverage effect. Therefore, the investors should be careful, particularly to good news and bad news, while deciding the investment. Except for September, the study did not find any strong signs of any other months. Hence, prediction by the investors becomes difficult. Integration of domestic markets with foreign markets may be responsible for this phenomenon. The most important implication that can be drawn from this study is that the past return plays a significant role in deciding today's return in the presence of month dummies. The ARCH and GARCH parameters are also found highly significant in the variance equation. Hence, one should take care of past volatility in his/her strategies for stock market investment. The asymmetric models outperform the symmetric models. Finally, except for few months, the study found no significant effect of other months on the return series which implies that the Indian stock market is becoming fairly efficient. To corroborate the findings of this study, a survey among the investors can be carried out in the future which can assess their perception towards these types of anomalies.

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Further reading

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