Estimating the Sensitivity of Stock Market: An Application of Asymmetric GARCH Models

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Abstract

Trading in stocks is filled with uncertainty and risk associated with extent of changes of an asset's value, magnitude of which is expressed as volatility. A substantial change in either direction in the price of an asset over a short period of time can be occurred due to higher volatility. The sensitive nature of market makes it decisive to study the volatility of market consistently for resolving the exact situation of the market. Analysis for stock market volatility has immense importance for all participants like policy makers, investors and companies who deals in stock markets. The application of appropriate models can measure the behavior and nature of volatility in accurate and acceptable way. The objective of this paper is to examine the nature of volatility in the India stock market and for this purpose the barometer of Indian stock market i.e. Sensex has been considered. The study is based on daily data of Sensex and widely accepted asymmetric GARCH models have been applied to study the nature of volatility. The findings of the paper indicate that there is time varying aspect in the Sensex volatility. However more effect is observed from previous days' information about return volatility. It is also extracted that negative shocks create more volatility in daily Sensex return in comparison with positive shocks. These are useful for various participants for whom risk and stock prices volatility factors plays important role in their decision making process.

Keywords: *Volatility, Sensex, GARCH, Stock Price.*

INTRODUCTION

Stock market volatility plays immense role in investment decisions, but uncertain to predict in different time periods. Volatility shows tendency of change in stock prices. Today, international financial system is changing rapidly and investment prospects are increasing, which leads the risk factor in stock markets and finally affects the investment decisions. In efficient stock markets where stock prices reflect changes according to up-to-date information, volatility has been recognized vital. Stock volatility also reacts with the irregular entrance of news in stock markets. Trading in stocks is filled with uncertainty and risk associated with extent of changes of an asset's value, magnitude of which is expressed as volatility. A substantial change in either direction in the price of an asset over a short period of time can be occurred due to higher volatility (Prashant Joshi, 2011). The sensitive nature of market makes it decisive to study the volatility of market consistently for resolving the exact situation of the market. Understanding of volatility is critical to each and every participant and authority who deal in stock markets. Policy makers take several steps with the consideration to increase investment and efficiency of stock markets for the economic development and estimate regarding volatility is first pillar for appropriate use of resources. Stock price volatility indicates efficiency level of stock markets. Study of volatility in stock prices is also serious for the proper financial systems to companies. Therefore, it is crucial to understand the nature of stock market volatility to access for smooth functioning in stock markets and economic growth. It is found by researchers in case of Indian markets / the markets of

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other nations that the volatility is a time varying factor and it needs to be analysed consistently to establish the exact situation of the market (Li & Hong, 2011). Modeling the volatility has been vigorous issues in the field of researches on stock markets and there are various models to understand the tendency of volatility. GARCH models are widely used econometric models which estimate the regular volatility of stock markets for a particular one time period. These models consider that volatility takes place in gaps or in clusters of time and it is time varying. Previous studies on GARCH models have different views regarding the usefulness of this model though many studies indicates that this model is good enough to estimate the tendency of stock market volatility and to describe various issues in stock market volatility. However, some studies focused on the conclusion that availability of both good and bad information consequences for change in different volumes in stock prices means asymmetric volatility in stock prices is present (Kaur, 2004). Therefore, GARCH models having asymmetric nature are more suitable for the analyses of volatility. The main concern of this paper is to measure the sensitivity of market by employing asymmetric GARCH models. Therefore, the objective of this paper is to examine the behaviour of volatility of Indian Stock market and investigate the effect of news with the help of asymmetric GARCH models. Estimating the stock market volatility is valuable for companies, policy makers, investors and other users to proceed under stock behavior in Indian stock markets. This study will serve for the decision making regarding investment and different issues of the stock market.

OBJECTIVES OF THE STUDY

The main concern of this paper is to measure the sensitivity of market by employing asymmetric GARCH models. Therefore, the objectives of this paper are as follows:

1. To examine the behaviour of volatility of Indian Stock market.
2. To investigate the effect of news with the help of asymmetric GARCH models.
3. To find out the best fitted GARCH model for measuring the sensitivity of Indian stock market.

REVIEW OF LITERATURE

Various studies identified the nature of volatility of stock market of India and found that volatility is the main aspect to understand while going for an investment in the market.

Mohanty and Kamaiah (2000) analyzed the volatility of thirty scrips traded in BSE Sensex with the help of the daily closing price and GARCH family models like ARCH (5), GARCH (1,1)- M and GARCH (1,1) models were applied. Analysis revealed the presence of ARCH effect in most of the scrips with the persistence of time varying volatility which was observed by ARCH (5) model. Return of security was found insignificantly affected by volatility with the help of GARCH (1, 1)-M model. This study did not check leverage effect by employing asymmetric GARCH models which was found to be one of the limitations of this study.

Kaur (2004) investigated the behaviour of the volatility of stock market of India (Sensex and Nifty) and results of the study indicated the presence of time varying volatility in Indian stock market. It is also revealed that the month of February and March were highly volatile with the highest return and highest conditional volatility. Study found that Wednesday was the day of higher returns with lower volatility and it was found a good day to invest.

Padhi (2006) identified time varying volatility for the stocks of fifteen companies and Sensex & Nifty and companies were short-listed from the sectors of Electrical, Power Plants, Electronics, Non-metallic, Diversified and Machinery. Daily closing price of these companies & indices were considered and results proved the presence of leverage effect. Long persistence of volatility was observed by applying GARCH (1,1) model. The coefficient of leverage term was negative & statistically significant and presence of asymmetric effect was also found by E-GARCH and GJR-GARCH models and persistence of higher volatility was shown by Electronics sector.

Joshi and Pandya (2008) recognized the nature of volatility of Indian stock market (BSE) by considering the daily data of sixteen years. Box-Jenkins methodology proved Autoregressive Moving Average structure for the process of error generating. Researchers applied ARCH and GARCH models to identify the volatility and observed that volatility clustering is satisfactorily explained by GARCH (1, 1) model. Results proved that BSE Sensex expressed mean reverting behaviour, volatility clustering and persistence of volatility.

Malik (2011) has found the effect of good news on the volatility of stock market and identified that good news decreases the volatility under the asymmetric GARCH model. The results of the study were in the similar nature and validated the findings with Monte Carlo simulations of volatility persistence with asymmetric effects and the researcher has created better implication for framing more advance asset pricing models for forecasting the stock market volatility. All these studies presented the different aspect of the behaviour of markets and focused on time varying nature but these studies are enough to predict the volatility of the market in current time, therefore this study is framed to identify the nature of volatility of Indian stock market for the improvement of the earlier studies.

RESEARCH METHODOLOGY

In order to provide sufficient explanation concerning sensitivity of Indian stock market, asymmetric GARCH models have been employed. The paper employs the use of asymmetric GARCH models i.e. EGARCH and TGARCH models to go into the depth of the volatility in stock prices. Usually, times series are assumed to be of non-stationary nature, so ADF and PP test have been applied to check stationarity of time series data for avoiding the spurious results. Descriptive statistics and diagnostics tests have also been employed to choose the best fitted model in Indian stock market for volatility. As Sensex is among oldest stock markets, it has been selected for this study. The study is based on secondary data which has been extracted from the official website of Bombay Stock Exchange (BSE). The study has considered the data from March 1, 2005 to February 29, 2016 for measuring the extent of volatility. EViews has been employed to apply the GARCH models.

Asymmetric GARCH Models for measuring volatility

Volatility is checked with various ways including the techniques of econometrics. GARCH models are having extensive usage in case of financial studies and these models are useful for forecasting the volatility. On the other hand, one of the limitations of the standard GARCH model is its assumption which focuses on the symmetric impact of positive and negative news. Although, Black (1976) and various other researchers have argued on asymmetries in the effect_which are attributed to leverage effect which shows negative shocks in the market is likely to affect volatility more than positive shocks. Hence, a number of extensions of the standard GARCH model like TGARCH, EGARCH, PGARCH and GARCH-mean have been recommended. In this paper, the conditional heteroskedastic models of econometrics which are named as asymmetric GARCH models have been used for the purpose of empirical analysis of volatility in stock market. In the current research paper asymmetric model of the GARCH family proposed by Nelson (1991) i.e. EGARCH has been applied. EGARCH contains asymmetric consent and some extra features like this model contain log specification, hence parameters of the model need not to be imposed with artificial non negative constraints. The specification of the model is as follows:

$$\log(h_t^2) = \omega + \alpha\left|\varepsilon_{t-1}/h_{t-1}\right| + \gamma(\varepsilon_{t-1}/h_{t-1}) + \beta\log(h_{t-1}^2) \qquad \text{.......(1)}$$

Here, left side of the equation represents the log of conditional variance and hence, confirms no negative variance term. Parameter α explains the size effect or effect of shock on volatility i.e. termed as GARCH effect, β presents the conditional volatility or effect of previous days volatility and γ measures the sign effect. $\gamma \neq 0$ is the evidence of the asymmetric impact of news on conditional variance. $\gamma > 0$ demonstrates the impact of good news and $\gamma < 0$ for the impact of bad news. An another variant on GARCH is Threshold GARCH (TGARCH) model to measure the asymmetry between up and down moves which followed the study of Glosten, Jagannathan, and Runkle (1993):

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \gamma_1 S_{t-1} a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where

$$S_{t-1} = \begin{cases} 1, & \text{if } a_{t-1} < 0; \\ 0, & \text{if } a_{t-1} \geq 0. \end{cases}$$

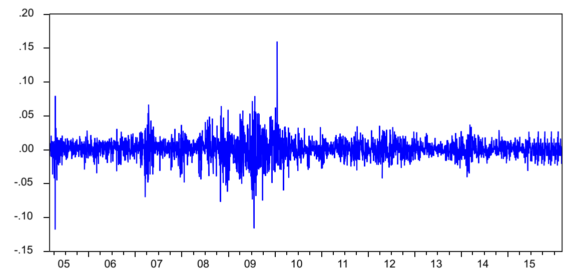
-------- (2)

Here, parameter γ_1 confirms the leverage effect when γ is significantly different from 0. Further, it can also be said that there is a fact of asymmetric effects in time-series, if γ_1 coefficient is not negative. Other parameters stand for the similar nature as EGARCH model.

Empirical Analysis and Results

It is pertinent to perform diagnostics teats, descriptive statistics and test of stationarity first to judge the nature of time series before applying asymmetric GARCH models. The results are presented in figure-1 and table- 1 for these tests. The fluctuations in data series of daily returns of Sensex have been plotted in figure- 1 for diagnostic testing. It is clearly depicted that the movements of returns are continuously in both the directions of mean line which is close to zero and fluctuations create time varying clusters. Hence, large fluctuations are followed by large fluctuations and small fluctuations are followed by small fluctuations for a continuous period which is same as Fama's (1965) observation. It can be found that volatility was up and down at different point of time with the positive and negative directions in clusters which give evidence that there is time varying clustering in returns and hence, justify the application of GARCH family models in this condition.

Figure 1 : DLNSENSEX



Descriptive statistics on Sensex return data series is calculated to observe the nature of data series for the application of models and the results are displayed in table- I which exhibits the significant variation in daily returns of Sensex and this has been measured with standard deviation. The mean value (0.0005) found to be very close to zero and confirms that the series is mean reverting which is usually expected for a time series return. The negative value of coefficient of skewness demonstrates the presence of large negative returns with non-symmetric and left tail distribution. Further, large value of kurtosis suggests leptokurtic distribution of the return. The normality of data series has been checked by Jarque-Bera statistics which is displayed in table- 1 and the probability value of Jarque-Bera statistics ($p < 0.05$) confirms the non- normal distribution of series and rejects the null hypothesis. Therefore, the results confirm the well recognized fact that daily return series is leptokurtic with the presence of skewness and non-normal distribution. The ARCH effect or presence of hetroscedascity has been checked by applying the ARCH-LM test with lag 1 under the assumption that there is no ARCH affect and the statistics of corresponding p value ($p = 0.000$) and observed R^2 value displayed in table-I suggests the evidence of ARCH effect in the residuals of the model. Hence, proves the rejection of null hypothesis and states the presence of heteroscedasticity in the return series.

Table 1 : Descriptive and Diagnostic Statistics

Statistic	DLSensex
Observation period	March 1, 2005 to Feb. 29, 2016
Number of observations	2869
Mean	0.000561
Std. Dev.	0.015368
Skewness	-0.0726
Kurtosis	12.07591
Jarque-Bera	9849.419 (0.0000)
ARCH-LM statistics (at lag =1)	117.029 (0.000)
Q(1) (autocorrelation of returns)	12.755 (2-tailed p=0.000)
Q2(1) (autocorrelation of returns squared)	115.23 (2-tailed p=0.000)
Q(36) (autocorrelation of returns)	82.852 (2-tailed p=0.000)
Q2(36) (autocorrelation of returns squared)	1413 (2-tailed p=0.000)

Further, Ljung Box statistics i.e. Q(k) and $Q^2(k)$ are used to examine the existence of the order of autocorrelation under the null hypothesis based on no autocorrelation in residuals of return and squared residuals respectively. The results present that p-values of Ljung Box statistic, Q(k) and $Q^2(k)$ indicate strong autocorrelation in the return and squared returns series. This suggests that residuals are conditionally heteroscedastic which provide the ground to run GARCH class models. Therefore, the results for return series clearly revealed that the series is not independence and normally distributed, but have presence of clustering volatility and ARCH effect.

1. Unit Root Test

The presence of unit root in the time series of daily return of Sensex has been checked by applying unit root tests namely ADF test and PP test. Further, Akaike Info Criteria (AIC) and Newey-West Bandwidth criteria have been utilized for the selection of optimum lag for tests. Both the tests work under the null hypothesis that series has a unit root. The results on unit root tests are reported in the table- II and outcome presented for ADF and PP tests at levels exhibits the acceptance of null hypothesis which shows the evidence of non- stationary Sensex data series at levels. But the results of tests at first difference prove that return series of Sensex rejects the null hypothesis at 1% level of significance for the presence of unit root. Hence, the series are found to be stationary at their first difference. Now, asymmetric GARCH models i.e. EGARCH and TGARCH have been applied to estimate and compare the volatility to find the best fit volatility model for Indian stock market.

Table 2 : Unit Root Tests

Variables	ADF Test		PP Test	
	(T-Statistic)	P-value	(T-Statistic)	P-value
Constant Level	1.661653	0.977	1.534151	0.9697
Firstdifference	-49.98017*	0.0001	-49.8674*	0.0001
Intercept Level	-0.736802	0.8356	-0.654582	0.8559

First difference	-23.52634*	0.000	-49.9155*	0.0001
Trend & intercept Level	-2.354239	0.4038	-2.20827	0.4842
First difference	-23.52469*	0.000	-49.9077*	0.000
Test critical values				
	Constant	Intercept		Trend & Intercept
1% level	-2.565890	-3.48606		-3.96176
5% level	-1.940951	-2.88586		-3.41163
10% level	-1.616614	-2.57982		-3.12768

Notes: '*' shows rejection of null hypothesis at 1 percent significance level.

2. Application of Box- Jenkins Methodology

There are two equations i.e. Mean equation and variance equation in GARCH family models. The residuals of mean equation of the model are the base for calculating the variance equation. In the first step, an appropriate mean equation is estimated by applying Box- Jenkins Methodology and then variance equation is calculated in the later phase by applying GARCH family models. The results of the Box- Jenkins Methodology have been displayed in table- II and LjungBox Q statistics is highly significant and indicate the presence of autocorrelation in the return series and squared return series. It is interesting to observe the patterns of autocorrelation function (ACF) and partial autocorrelation function (PACF) statistics. Diagnostics for ARIMA identifies that Sensex return series has significant AR and MA terms at lag 1.

3. Modeling of Volatility: Asymmetric GARCH-family Models

The analysis shows the presence of significant ARCH effect and volatility clustering and hence, gives the indication to estimate the conditional variance equation of residuals. GARCH process generates symmetric response function for the stock returns, although French, Schwert & Stambaugh (1987) and Christie (1982) have suggested that returns are likely to be more volatile in response to negative shocks to returns and less volatile in response to positive shocks. They captured the magnitude as well as sign effect which is showed as differential response in terms of leverage effect. In this direction, most popular asymmetric GARCH models (EGARCH and TGARCH) which examine the leverage effect have been employed to measure the volatility of daily return distribution. AIC and SIC criteria have been used for checking the appropriateness of order for conditional variance equation and (1, 1) process is observed as the best fitted order for the volatility models. The results of volatility models along with diagnostic statistics have been reported in table- 3 and table- 4. Table- 3 shows the results of EGARCH (1, 1) model and confirms the significant effect of news on return movement. As per the results, ARCH term (α) is found to be significant which means today's return volatility is influenced by previous days' Sensex return information.

The results displays that GARCH term (β) is also significant which indicates that today's return volatility is also influenced by previous days' volatility which means persistence of volatility has significant effect. Although, the coefficients of GARCH (β= 0.974) is observed higher than coefficients of ARCH (α= 0.197) which establishes that there is more effect of persistence of volatility on return volatility under normal distribution. Further, significant different from zero value of coefficient of leverage (γ= -0.090) at 1% level of significance explores the presence of leverage effect on Sensex volatility. Hence, indicates the existence of asymmetric effect of good news & bad news on Sensex volatility which implies that both the news do not have similar effect on the volatility of return. The negative value of coefficient of γ reveals that more volatility in returns generates lower returns and hence, confirms negative relationship of returns with volatility. Various studies like Padhi (2006) and Kumar & Sumanjeet (2006) have also observed the same results.

Another asymmetric model i.e. TGARCH (1, 1) model has also been applied on daily Sensex return series and the outcomes are presented in table- 4. This model is used to capture the sign effect along with leverage effect.

The result estimation of TGARCH model represents the significant value of the coefficient of leverage term (γ= 0.118). This value is found to be greater than zero which implies significant leverage effect which is similar to the results of EGARCH model. Overall, presents the different impact of bad and good news on volatility of returns. It is important to note that all parameters are significant and the sign of leverage term (γ) is positive which means Sensex returns are more responsive to bad news instead of positive news, since decrease in stock prices creates more risk of stock holding. The results of TGARCH model are also supported by the studies of Schwert (1989) and French et al. (1987).

Table 3 : Results of EGARCH (1, 1) Model

Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Prob.**
C	0.000528	0.000207	2.546044	0.0109
AR(1)	-0.05951	0.215267	-0.27646	0.7822
MA(1)	0.139286	0.214408	0.649631	0.5159
	Variance Equation			
C(4)	-0.37468	0.031517	-11.8881	0
C(5)α	0.19739	0.012346	15.98769	0
C(6)γ	-0.09045	0.008466	-10.6838	0
C(7)ß	0.974251	0.002919	333.7095	0
R-squared	0	Mean dependent var		0.000558
Adjusted R-squared	0	S.D. dependent var		0.01537
S.E. of regression	0.015368	Akaike info criterion		-5.91225
Sum squared resid	0.677372	Schwarz criterion		-5.89797
Log likelihood	8480.535	Hannan - Quinn criter.		-5.90461
Durbin-Watson stat	1.866591			

Table 4 : Results of TGARCH (1, 1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000595	0.000217	2.747342	0.006
AR(1)	-0.07594	0.247878	-0.30634	0.7593
MA(1)	0.149536	0.24653	0.606563	0.5441
	Variance Equation			
C	3.97E-06	4.90E-07	8.098746	0
RESID(-1)^2 (α)	0.037208	0.006586	5.649685	0
RESID(-1)^2*(RESID(-1)<0) (γ)	0.118974	0.013041	9.122834	0
GARCH(-1) (ß)	0.884703	0.007996	110.6435	0
R-squared	0.005314	Mean dependent var		0.000558
Adjusted R-squared	0.00462	S.D. dependent var		0.01537
S.E. of regression	0.015335	Akaike info criterion		-5.91639
Sum squared resid	0.673715	Schwarz criterion		-5.90184
Log likelihood	8487.792	Hannan-Quinn criter.		-5.90967
Durbin-Watson stat	1.866541			

4. Diagnostic Tests for Model Adequacy

Both the asymmetric GARCH models present the evidence of asymmetric effect of news on_volatility of returns. But, it is necessary to check the consistency of the model for the adequacy of estimation and this has been checked by most important diagnostic tests for volatility models. The results for adequacy of both the models are presented in table-5 and table-6. Firstly, presence of serial correlation has been checked by Ljung-Box, Q statistics to capture the volatility clustering phenomenon under the null hypothesis of no serial correlation in the residuals. Table- 5 exhibits the results of standardised squared residuals and corresponding p-value of Q statistics is found to be greater than 0.05 which states that the null hypothesis of no autocorrelation within standardised squared residuals can not be rejected. Hence, results produce evidence that the residuals calculated under the models are purely white noise. Hence, it can be concluded that models are strong in capturing volatility clustering.

Table 5 : Correlegram of standarized residuals and standarized residuals squared

	Lags	standarized residuals		standarized residuals squared	
		Q-Stat	**Prob**	**Q-Stat**	**Prob**
EGARCH	1	0.0647		0.3713	
	2	0.9511		0.4765	
	10	8.6322	0.374	16.796	0.072
	20	24.759	0.132	26.731	0.084
	30	29.53	0.386	32.414	0.258
	35	30.471	0.594	42.988	0.114
TGARCH	1	0.3856		1.4633	
	2	0.8987		2.1606	
	10	8.461	0.39	14.739	0.064
	20	23.457	0.174	20.77	0.291
	30	28.648	0.431	26.545	0.543
	35	29.887	0.623	39.21	0.211

Jarque-Bera test which measures the normality of standardised returns has also been applied under the null hypothesis that residuals are normally distributed. The results from normality test for both the models are displayed in table- 6. On the basis of p-value (< 0.05) of Jarque-Bera statistics, the null hypothesis is rejected in case of both the models. This presents that distributions of standardised returns are far from Gaussian normal distribution which supports the study of Joshi (2011).

In order to check the presence of heteroscedasticity in return series of volatility models, ARCH- LM test has been applied under the null hypothesis of no ARCH affect. The results displayed in table- 6 presented that both the volatility models fail to reject the null hypothesis of no ARCH effect as evident from F-statistics ($p > 0.05$). This represents no significant ARCH effect and hence, proves the fitness of volatility models. Hence, models are observed to be fit for capturing time varying volatility of Sensex.

Table 6 : Normality and ARCH-LM test

Normality of Standardized Returns	**EGARCH**	**TGARCH**
Jarque - Bera	581.539	683.057
Prob.	0	0
Heteroskedasticity Test: ARCH	**EGARCH**	**TGARCH**
F-statistic	0.370618	1.461045
P-Value	0.5427	0.2269
Obs*R-squared	0.370829	1.461319
P-value	0.5426	0.2267

Most appropriate model to capture the volatility in Indian stock market has been selected on the basis of information criteria and Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SIC) with log likelihood have been employed. The statistics of these criteria are reported. The statistics confirms that TGARCH model is the best fitted model to capture time varying volatility of Sensex return because the AIC & SIC values are found lower in case of TGARCH model and also contains high log-likelihood value. Overall, TGARCH model outperforms the EGARCH model.

CONCLUSION

This paper has made an attempt to test the sensitivity of Indian stock market by applying GARCH class models in reference to Sensex daily return. Results of the study revealed that Sensex volatility contains mean reverting behaviour and provides the evidence for the presence of volatility clustering and persistence of conditional volatility. The asymmetric GARCH model suggested more effect of persistence of volatility on Sensex volatility as previous days' information about return volatility has significant effect on Sensex volatility. Although, models suggested the impact of present day's news on volatility of Sensex return which means volatility has an influence of its own internal shocks. TGARCH model recommended that Indian stock market has leverage effect and hence, there is asymmetric news effect on volatility of Sensex which means negative shocks create more volatility in daily Sensex return in comparison with positive shocks. It is found that asymmetrical GARCH models performed better for Sensex volatility and TGARCH model is observed as the most appropriate model to capture time varying volatility of Sensex return. The findings of the study are useful for the investors as the time varying nature of volatility of Indian stock market is observed and investors are recommended to study the volatility of market before planning for an investment.

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