

Sectoral Analysis of Bombay Stock Exchange – Application of Garch Models

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ABSTRACT

The present work used GARCH (1,1), TGARCH (1,1) and EGARCH (1,1) models for studying the volatility persistence and volatility clustering behaviour and leverage effect for the daily returns of the five sectoral indices of BSE Sensex mainly FMCG, I&T, Auto, Healthcare, Oil & Gas along with BSE Sensex. The results revealed that the news about the volatility in the previous period and lagged conditional variance impact significantly the volatility of the daily return series (of the five sectoral indices and BSE Sensex) in the current period. The leverage effect showed that bad news impact significantly the current volatility than the good news of the same magnitude. Oil & Gas and I & T sectors have shown more volatility persistence behaviour and slower decay of volatility compared to the Auto, FMCG and Healthcare. It is suggested that the government and regulatory bodies of stock markets need to take necessary steps to avoid the high volatility behaviour of the stock indices of Bombay Stock Exchange in order to protect the interest of the foreign and domestic investors.

Keywords: Volatility Clustering, Leverage effect, GARCH, ARCH, BSE Sensex.

INTRODUCTION:

Financial Market plays a very important role in financial health of an economic system as it is the primary source of capital required for varied economic activities. The importance of the financial markets has become all the more significant due to Liberalisation and Globalisation policies encouraging players from all over the world to participate in the financial markets. In view of this financial markets are considered as the economic barometer of a country. Stock markets are influenced by numerous socio-economic and political factors which are interacting with each other continuously and simultaneously all over the world. As a result of this volatility has become a common phenomenon of the financial markets reflecting the happenings around the world. But volatility in stock markets influence the various stake holders like, domestic and foreign investors, companies, governments and policy makers by impacting the asset pricing, returns on assets, portfolio management and risk associated with the volatility. This volatility feature of stock markets has caught the attention of researchers resulting into development of various models to analyse the volatility dynamics of financial markets. The important and popular models developed in the process are Auto Regressive Conditional Heteroscedasticity (ARCH) by Robert Engle (1982) and Generalised Auto Regressive Conditional Heteroskedastic (GARCH) by Bollerslev (1986) which are very widely used in the literature for understanding the volatility dynamics in terms of volatility clustering and persistence behaviour and leverage effect. The present study aims to study the volatility dynamics present in the Bombay Stock Market (BSE). BSE is an Indian Stock Market located at Mumbai, which is known as the financial capital of the country. BSE is considered as an important stock exchange in terms of market capitalisation more than \$ 2 trillion in 2017 (Wikipedia). During 2015 S&P Dow Jones and BSE together launched S&P BSE All Cap Index Family in response to the market need (bseinida.com). The BSE All Cap index is comprising of ten sub-indices based on the different sectors. The main purpose of these indices is to facilitate the investors with an instrument to analyse market movements

across different sectors so as to enable them to make effective investment decisions. The sectoral indices launched are Basic Materials, Auto, Healthcare, FMCG, Information Technology, etc. In the present analysis an effort has been made to study the volatility dynamics of five sub sectors mainly Auto, FMCG, Healthcare, Oil & Gas and I&T along with the BSE main index Sensex using GARCH models. Lot of policy changes have been taken place in these sectors over a period of time. In view of this the current analysis will be of immense help to the investors, regulators and policy makers in understanding the sectoral movements.

LITERATURE REVIEW:

This section discusses the various studies done in the literature on volatility dynamics of stock markets using GARCH models which have paved the way for our analysis in the present study.

Srinivasan & Ibrahim (2010) forecasted Stock Market Volatility of BSE-30 Index with the help of GARCH models based on the daily data and results led to the conclusion that symmetric GARCH (1,1) model performed better in forecasting the conditional variance of the Sensex daily returns compared to EGARCH (1,1) and TGARCH (1,1) models. Khemiri (2011) analysed the dynamics of four international stock indices by applying Smooth Transition GARCH (STGARCH) model. The results showed that in Logistic Smooth Transition GARCH (LSTGARCH) model return shock's sign on asymmetric conditional volatility is stressed and Exponential Smooth Transition GARCH (ESTGARCH) model highlighted the price shock's magnitude effect on the subsequent volatility. Ahmed & Suliman (2011) used GARCH models to study the conditional variance volatility in the daily returns of the Khartoum Stock Exchange of Sudan. The study done the analysis based on the both symmetric and asymmetric models of GARCH. Empirical analysis indicated that the conditional variance process followed the explosive process and their existed risk premium for the return series. Further it was found that the asymmetric models fitted better to the data compared to symmetric models. Takaishi (2013) used GARCH model to investigate the volatility of a financial spin model with three stages. For this purpose, author used Bayesian Inference performed by the Markov Chain Monte Carlo (MCMC) Method. The analysis indicated the volatility clustering exhibited by the volatility of the spin financial market, the situation often found in the real financial markets. Savadatti (2018) analysed the pattern of volatility in daily returns of the BSE index employing symmetric and asymmetric GARCH models and results revealed the existence of volatility clustering behaviour and leverage effect. Malik & Hassan (2004) studied how different events influence the volatility pattern of assets in the financial markets and persistence of volatility was impacted by the unanticipated shocks over time using Iterated Cumulated Sum of Squares (ICSS) algorithm for five major sectors and authors opined that their results had important implications for financial market functioning. Many studies have used the family of GARCH models to study the volatility dynamics of different stock indices (Adson, 2013, Singh & Teena, 2018). Based on the literature review keeping in view the objective, the theoretical underpinning of the present analysis has been discussed in the next section.

RESEARCH METHODOLOGY:

Data:

The present study used daily closing prices of the five sectoral indices of the S&P BSE and Sensex for the data analysis. The data pertained to seventeen years three months 12 days (03-01-2000 to 12-04-2018) resulting into 4553 observations excluding public holidays, for six indices each namely S&P BSE FMCG, S&P BSE I & T, S&P BSE Auto, S&P BSE Health care, S&P BSE Oil & Gas and S&P BSE main index Sensex. The required data were collected from BSE website – bseindia.com. The time series analysis is carried out with the help of statistical software e-views 9. For the time series analysis, the daily closing prices of all the six indices are converted into daily return series using the following formula

$$R_t = \log \left(\frac{P_t}{P_{t-1}} \right) \text{-----} (1)$$

Where R_t indicates the daily returns of the six indices of BSE at time 't'. P_t and P_{t-1} are daily closing prices of the selected six indices at time 't' and 't-1' respectively.

Theoretical Framework:

The theoretical framework essential for the analysis is detailed in this section.

Descriptive Statistics:

To study the properties of the series under consideration the descriptive statistics comprising of mean, standard deviation, skewness, kurtosis, Jarque-Berra tests have been used.

Unit Root Test:

Once distributional features of the series are made to be known with the help of descriptive statistics next step is to test for stationarity properties of series. The further analysis of the data requires that the series under consideration have to be stationary. Hence, Augmented Dicky Fuller Test (ADF, 1979) has been used for the purpose of testing the stationarity of the series.

ARCH-LM Test:

Auto Regressive Conditional Heteroscedasticity –Lagrange Multiplier test is employed to exam the presence of heteroscedasticity in residual series of the daily returns of the six indices of BSE respectively. The presence of heteroscedasticity is a pre-requisite for using the GARCH model to capture the volatility behaviour present in the selected indices' daily returns. For this purpose, the residuals of the return series are obtained by running the mean equation as stated in equation (2) for daily closing prices of selected six indices of BSE.

GARCH Models:

The present paper's main objective is to analyse the sectoral volatility of S&P BSE Indices. For this purpose, the time series technique called Generalised Conditional Auto Regressive Conditional Heteroscedasticity (GARCH) Technique is used to analyse the data pertaining to daily return series of the five sectoral indices of S&P BSE along with Sensex index. GARCH models are used extensively in literature to study the volatility analysis of financial time series data. GARCH models are categorised into two, symmetric and asymmetric models. In symmetric models the good and bad news are treated symmetrically hence, both the news has same effect on the conditional volatility. The important symmetric GARCH models are GARCH and GARCH in Mean (GARCH-M) model. In asymmetric models the effect of bad news and good news on the conditional variance is considered since, it is perceived that in financial markets negative shocks have greater effect on the volatility than the positive shocks. Hence, leverage effects are observed in stock returns which are captured by asymmetric models. The important asymmetric models are T-GARCH, E-GARCH and P-GARCH models. In the present paper GARCH (1,1), T-GARCH (1,1) and E-GARCH (1,1) models have been used for the data analysis. The details of these models are discussed below.

In GARCH models two equations have to be estimated one is mean equation and other is conditional variance equation. The mean equation used for all GARCH models is specified as below

$$R_t = \delta + \varepsilon_t ; \text{Mean Equation} \text{-----} (2)$$

Where R_t is the daily return series of an index under consideration at time 't', δ is the mean returns and ε_t is the residual return. The conditional variance equation for the different GARCH models used in the present analysis are explained below.

GARCH (1,1) Model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \text{-----} (3)$$

The above equation is the conditional variance equation used to study the symmetric behaviour of volatility (irrespective of signs) in daily returns of different sectoral indices of BSE during the study period (Bollerslev, 1986). Here σ_t^2 is the dependent variable –conditional variance term and independent variables are, ε_{t-1}^2 is the squared error term at 't-1' time (lagged ARCH term) and σ_{t-1}^2 is the lagged conditional variance (GARCH) term. α_1 is the ARCH parameter and β is the GARCH parameter and α_0 is the intercept. If $(\alpha_1 + \beta) > 1$ means volatility is not converging over a period of time, if $(\alpha_1 + \beta) < 1$ then volatility is a mean reverting process and converges over a period of time and if the sum is close to 1 it implies volatility is persistent and clustering behaviour. Here the coefficients have to satisfy the condition of $\alpha_0 > 0, \alpha_1 \geq 0, \beta \geq 0$.

T-GARCH (1,1) Model:

In symmetric GARCH models squared of the residuals are taken as independent variable resulting into ignoring the signs. But, it is observed that the volatility in stock markets are influenced more by bad news (negative shocks) than the good news (positive shocks) hence, to capture the leverage effect observed in financial time series specially in stock returns the asymmetric GARCH models are used very widely. Threshold GARCH (T-GARCH) model is an asymmetric model used in the present study to capture the effect of leverage on the volatility of the daily returns of the different indices of BSE. The mean equation is as stated in (2). The conditional variance equation of the model is detailed below (Glosten, Jagannathan & Reunkie, 1993; Zakoian, 1994).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 \text{-----} (4)$$

Where, $\alpha_1 > 0, \beta > 0, \gamma > 0$ and α_1 & β are ARCH and GARCH coefficients respectively and γ is the

parameter which captures the leverage effect. If the shock is positive (good news) then the effect on volatility is α_1 ($I_{t-1} = 0$) and if the shock is negative (bad news) the effect on volatility is $\alpha_1 + \gamma$ ($I_{t-1} = 1$). If $\gamma > 0$ then it is said that there is leverage effect on the volatility.

E-GARCH (1,1) Model:

The conditional variance equation of the Exponential GARCH (E-GARCH) model is given as (Nelson, 1991)

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln \sigma_{t-1}^2 - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \text{-----(5)}$$

Here, α_1 is ARCH parameter, β is GARCH parameter and γ is parameter capturing the leverage effect. If γ is less than zero means there is leverage effect in the return series. Negative shocks' influence is larger than the positive shocks on the conditional variance.

RESULTS AND DISCUSSIONS:

Descriptive Statistical Analysis:

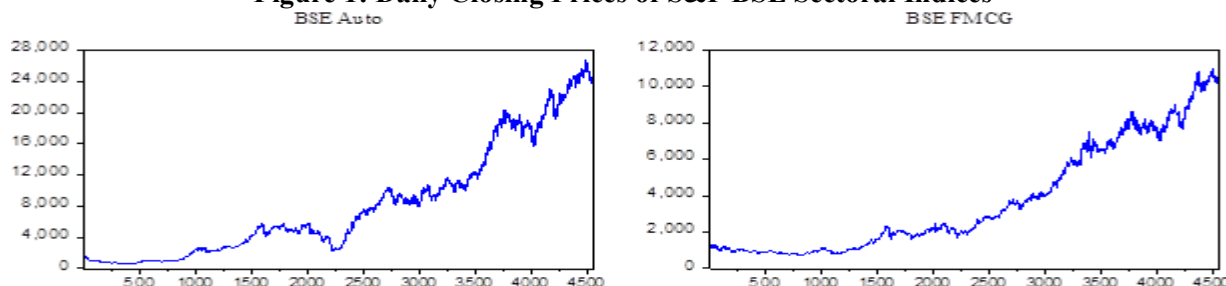
The plots of the closing prices of the selected six indices of BSE are presented Figure 1. The figure shows that lot of volatility is observed in the closing prices of FMCG, I&T, Auto, Health care, Oil & Gas and Sensex revealing that closing price series may not be stationary. All the series portrayed increasing trend in closing prices during the study period with lot of fluctuations. Hence, closing prices of various indices have been converted to return series using the formula presented in equation (1) and then the plots of the return series are presented in Figure 2. It is very clear from the figure that all the return series pertaining to six indices exhibiting lot of sustained high volatility followed by the sustained low volatility indicating volatility clustering in the return series. To understand the distributional properties of the return series of the selected indices various descriptive statistics have been calculated and shown in the Table 1.

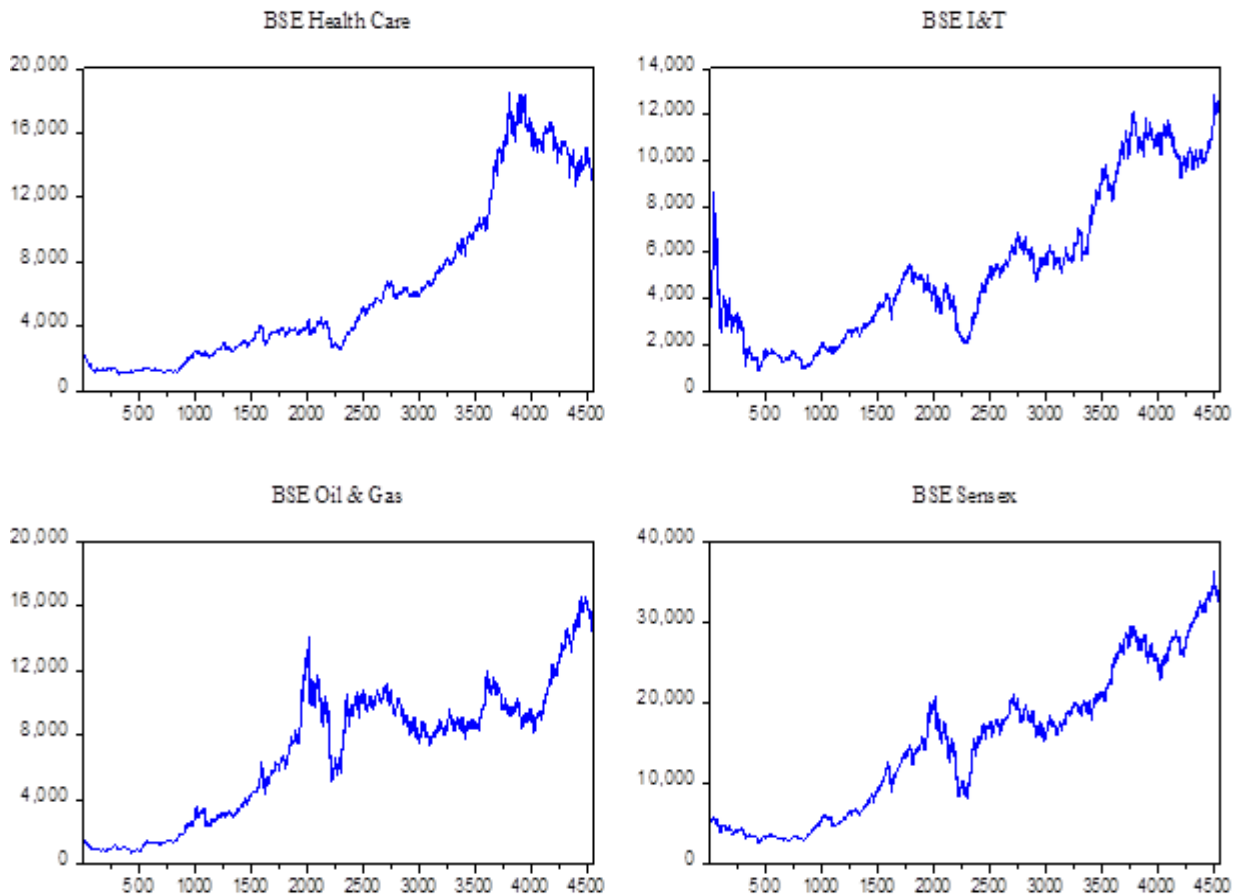
Table 1: Descriptive Statistics for Daily Returns of Sectoral Indices of BSE

	FMCG	Health care	I & T	Oil & Gas	Auto	Sensex
Mean	0.000485	0.000396	0.000240	0.000503	0.000640	0.000406
Median	0.000651	0.000868	0.000411	0.000629	0.001110	0.000937
Maximum	0.083990	0.077494	0.145016	0.174845	0.106266	0.159900
Minimum	-0.111474	-0.086753	-0.222984	-0.162111	-0.110126	-0.118092
Std. Dev.	0.013538	0.012702	0.022339	0.017666	0.015090	0.014751
Skewness	-0.216088	-0.537721	-0.467801	-0.370240	-0.343566	-0.204381
Kurtosis	7.529377	8.067879	11.18253	11.60952	6.668940	10.70883
Jarque-Bera	3925.623	5089.531	12862.11	14159.71	2642.096	11302.83
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	4551	4551	4551	4551	4551	4552

It may be seen from the Table 1 that the mean return is highest for Auto followed by Oil & Gas, FMCG, Sensex, Health care and I & T respectively. Mean return is lowest for I & T index. The standard deviation which measures the volatility in the return series show that highest volatility is observed in I&T sectoral index followed by Oil & Gas, Auto, Sensex, FMCG and Health care. The volatility clustering can be seen from the Figure 2 which shows the volatility persistence behaviour of the return series for all the six indices during the study period. Skewness calculations for all the six indices are having negative sign and Kurtosis are much above 3 indicating that the return series for all the six indices are not normally distributed but

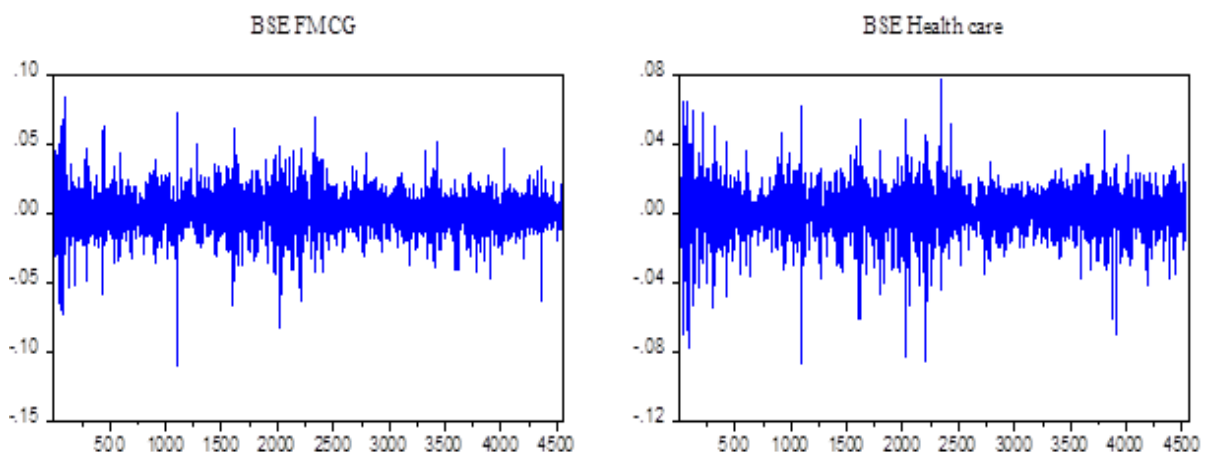
Figure 1: Daily Closing Prices of S&P BSE Sectoral Indices





leptokurtic with left tail. Jarque-Bera Statistics calculated for all the indices are also indicative of the decision that series are not normally distributed as the probability is low resulting into rejection of null hypothesis of normality assumption. The Quantile-Quantile graph presented in Figure 3 validates the inference drawn on the results of descriptive statistics as the blue lines shown in the Figure are following S shape rather than the 45-degree straight line confirming that return series are not normal.

Figure 2: Daily Returns of S&P BSE Sectoral Indices



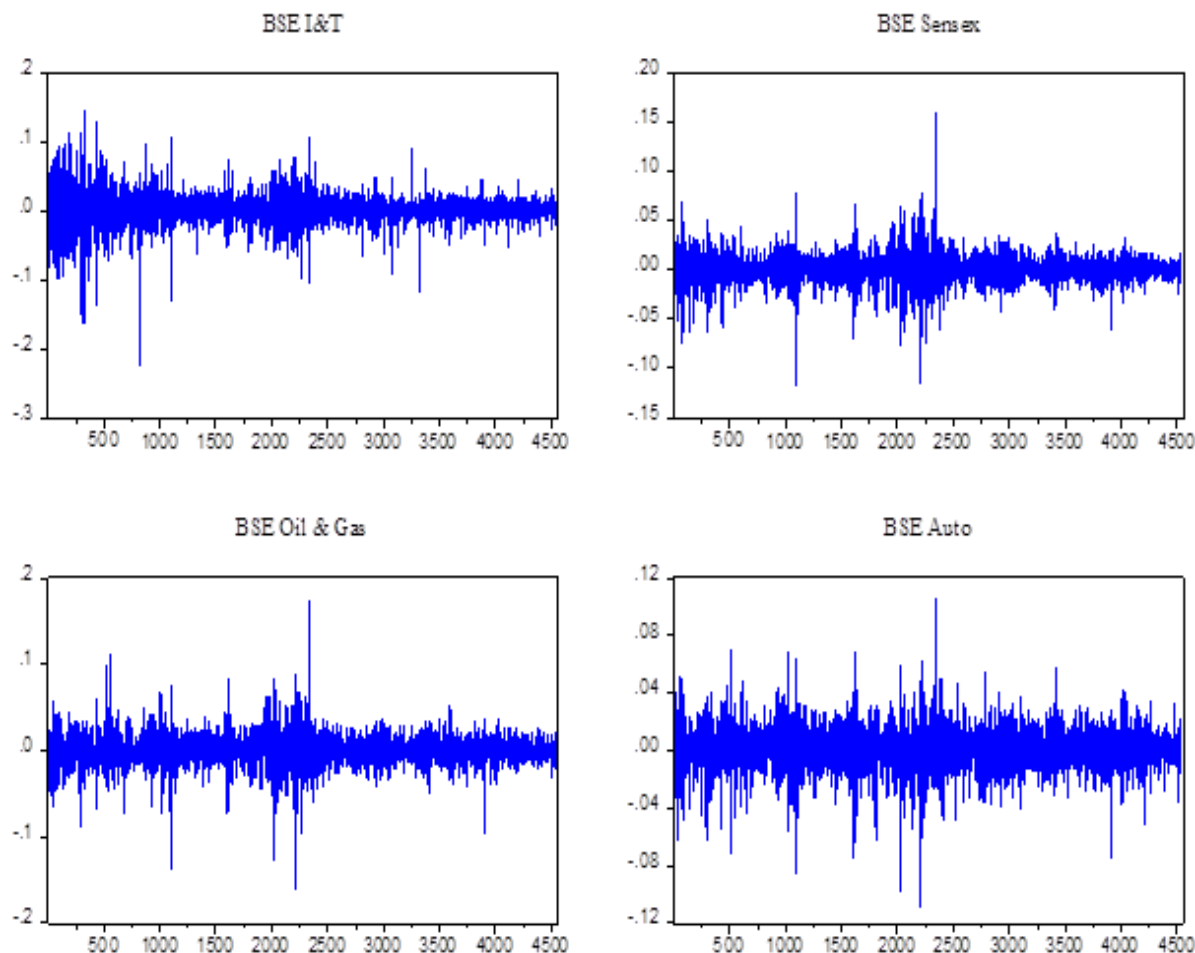
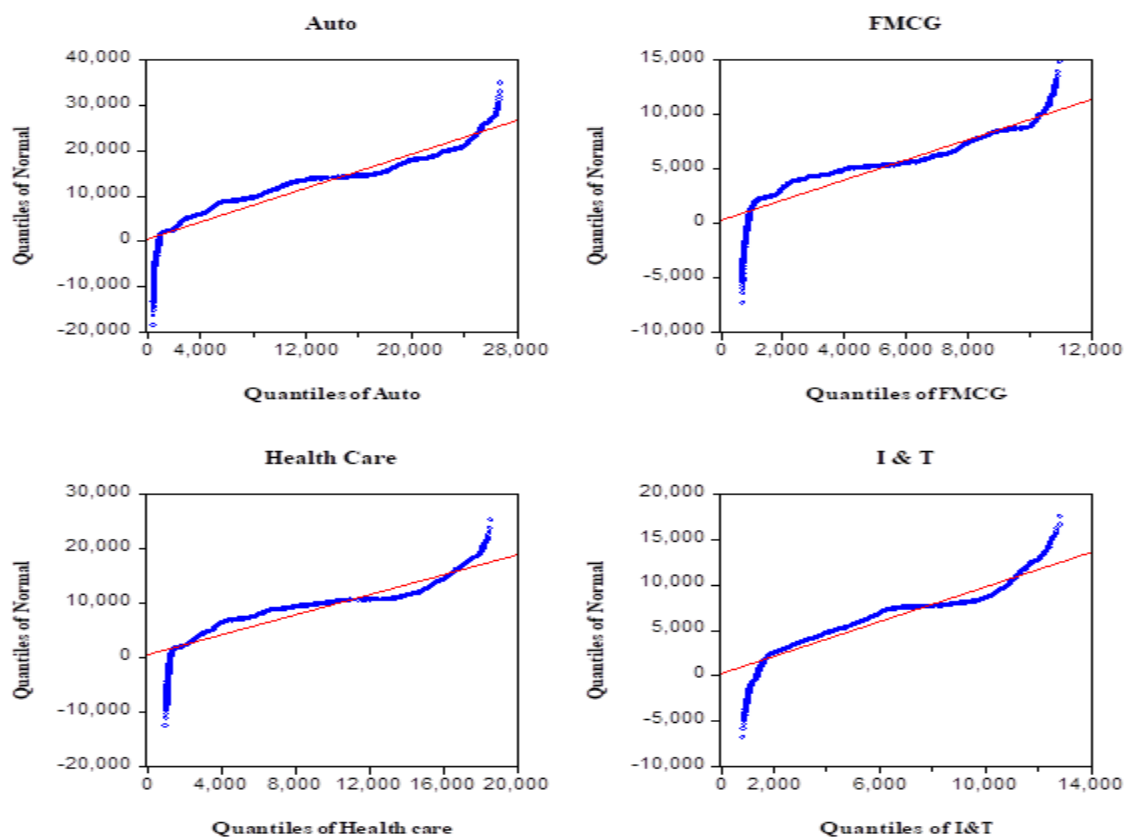
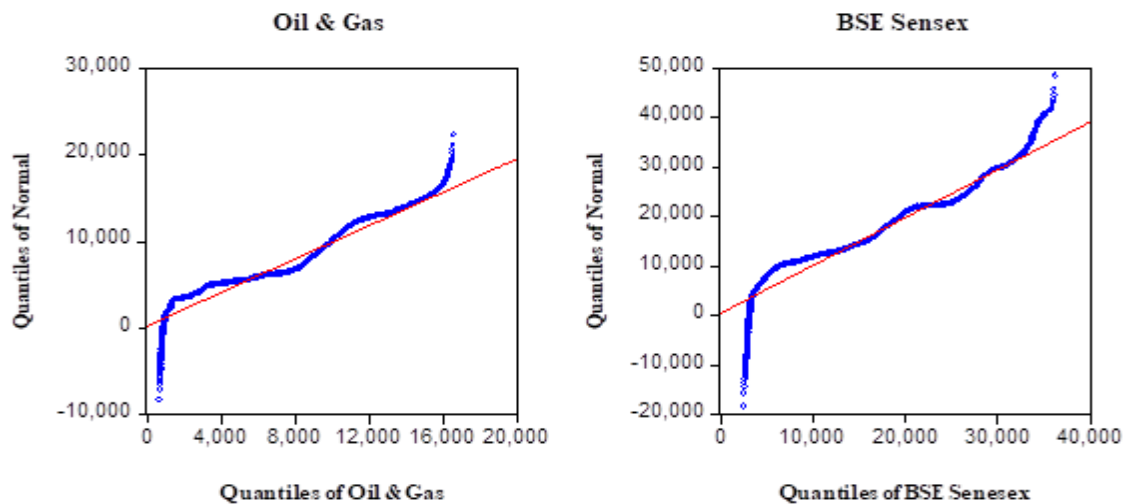


Figure 3: Quantile – Quantile Plot of Daily Returns (S&P BSE Sectoral Indices)





In order to apply GARCH model for studying the volatility pattern present in daily returns of the six selected indices of BSE it is necessary to ensure that the series under consideration are stationary and for which ADF test has been used and the results of the same are shown in the Table 2.

Table 2: ADF Unit Root Test Results (Daily Returns of BSE Sectoral Indices)

FMCG			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-64.66059	0.0001
	Test critical values:	1% level	-3.431604	
		5% level	-2.861979	
		10% level	-2.567047	
I & T			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-62.14793	0.0001
	Test critical values:	1% level	-3.431604	
		5% level	-2.861979	
		10% level	-2.567047	
Auto			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-58.89785	0.0001
	Test critical values:	1% level	-3.431604	
		5% level	-2.861979	
		10% level	-2.567047	
Health Care			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-59.84649	0.0001
	Test critical values:	1% level	-3.431604	
		5% level	-2.861979	
		10% level	-2.567047	
Oil & Gas			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-47.53589	0.0001
	Test critical values:	1% level	-3.431605	
		5% level	-2.861979	
		10% level	-2.567047	
BSE Sensex			t-Statistic	Prob.*
	Augmented Dickey-Fuller test statistic		-62.77124	0.0001
	Test critical values:	1% level	-3.431604	
		5% level	-2.861979	
		10% level	-2.567047	

*MacKinnon (1996) one-sided p-values.

It may be seen from the Table 2 that all the six indices' return series are stationary as the ADF test statistics calculated for all the indices are higher than the critical values at 1% significance level. Hence, it may be concluded that the daily return series of the selected indices of BSE are stationary. Next it is necessary to check for the existence of ARCH effect if any in the residuals of the daily return series of the selected indices and the residuals are derived by running the mean equation for return series. ARCH –LM test is used to test for the presence of heteroscedasticity in residuals of return series and the results of the same are contained in Table 3.

Table 3: Heteroscedasticity Test – ARCH (Residuals of daily returns)

FMCG	F-statistic	109.9881	Prob. F(5,4540)	0.0000
	Obs*R-squared	491.1708	Prob. Chi-Square(5)	0.0000
I & T	F-statistic	157.7218	Prob. F(5,4540)	0.0000
	Obs*R-squared	672.7866	Prob. Chi-Square(5)	0.0000
Auto	F-statistic	137.2372	Prob. F(5,4540)	0.0000
	Obs*R-squared	596.8791	Prob. Chi-Square(5)	0.0000
Health Care	F-statistic	145.2601	Prob. F(5,4540)	0.0000
	Obs*R-squared	626.9604	Prob. Chi-Square(5)	0.0000
Oil & Gas	F-statistic	92.82811	Prob. F(5,4540)	0.0000
	Obs*R-squared	421.6474	Prob. Chi-Square(5)	0.0000
BSE Sensex	F-statistic	106.8870	Prob. F(5,4541)	0.0000
	Obs*R-squared	478.7918	Prob. Chi-Square(5)	0.0000

It is revealed from the results presented in Table 3 that Chi-Square probability is quite low i.e., lower than 0.05 indicating the rejection of null hypothesis in all the six selected indices hence, to be concluded that there exist ARCH effects in the residuals of the daily return series of all the indices. This paves the way for using the GARCH models for the analysis of the pattern of volatility present in the daily return series of the six selected indices of BSE.

GARCH (1,1) Model:

The results of the GARCH (1,1) model of all the indices are presented in Table 4. All the estimated coefficients of mean and conditional variance equations are statistically significant. Especially ARCH and GARCH coefficients are significant and having expected sign in case of all the six indices of BSE. This indicates that news about previous period's volatility and previous periods' volatility significantly impacting the volatility pattern in the return series during the current period in all the selected indices. The sum of ARCH and GARCH coefficients is highest for the BSE Sensex (0.990084) followed by Oil & Gas (0.988392), I&T (0.983043), Auto (0.965496), FMCG (0.957359) and Health care (0.956821) respectively. The values of $\alpha_1 + \beta$ (ARCH+GARCH) are less than one indicating mean reverting process but since the sums are close to 1 indicating a slow convergence of the volatility. The model adequacy requires that the residuals are to be tested for the presence of ARCH effect which has been done with the help of ARCH-LM test and the results of the same for the Sensex and five sectoral indices are presented in the Table 4. The probability value for Sensex and all other five indices are higher than 0.05 causing the acceptance of null hypothesis of no ARCH effect hence, concluded that estimated GARCH models are adequately explaining the volatility behaviour of the five sectoral indices and Sensex.

Table 4: GARCH (1,1) Model Results

Sectoral Index	Equation/ Test	Variable	Coefficient	Std. Error	z-Statistic	Prob.#	Inference
FMCG	Mean Variance	δ	0.000707	0.000165	4.292229	0.0000	
		α_0	7.71E-06	7.43E-07	10.37977	0.0000	
		α_1 (ARCH)	0.116978	0.006609	17.69856	0.0000	
		β (GARCH)	0.840381	0.008550	98.29533	0.0000	
	ARCH-LM Test	F-statistic	1.338144	Prob. F(5,4540)		0.2449	No ARCH
		Obs*R-squared	6.689702	Prob. Chi-Square(5)		0.2448	

Sectoral Index	Equation/ Test	Variable	Coefficient	Std. Error	z-Statistic	Prob.#	Inference
I & T	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000987	0.000224	4.414166	0.0000	
		α_0	9.36E-06	6.38E-07	14.67254	0.0000	
		α_1 (ARCH)	0.122902	0.005430	22.63513	0.0000	
		β (GARCH)	0.860141	0.006106	140.8702	0.0000	
	ARCH-LM Test	F-statistic	0.711203	Prob. F(5,4540)		0.6150	No ARCH
		Obs*R-squared	3.557929	Prob. Chi-Square(5)		0.6146	
Auto	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.001064	0.000178	5.959423	0.0000	
		α_0	8.17E-06	2.10E-06	3.891595	0.0001	
		α_1 (ARCH)	0.115377	0.019472	5.925275	0.0000	
		β (GARCH)	0.850119	0.025175	33.76814	0.0000	
	ARCH-LM Test	F-statistic	1.568323	Prob. F(5,4540)		0.1654	No ARCH
		Obs*R-squared	7.838441	Prob. Chi-Square(5)		0.1654	
Health Care	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000712	0.000147	4.830101	0.0000	
		α_0	7.05E-06	7.63E-07	9.240032	0.0000	
		α_1 (ARCH)	0.124662	0.007980	15.62253	0.0000	
		β (GARCH)	0.832159	0.010222	81.40625	0.0000	
	ARCH-LM Test	F-statistic	1.470635	Prob. F(7,4536)		0.1728	No ARCH
		Obs*R-squared	10.28925	Prob. Chi-Square(7)		0.1728	
Oil & Gas	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000632	0.000207	3.053376	0.0023	
		α_0	4.32E-06	5.24E-07	8.244463	0.0000	
		α_1 (ARCH)	0.087889	0.004515	19.46421	0.0000	
		β (GARCH)	0.900503	0.004443	202.6705	0.0000	
	ARCH-LM Test	F-statistic	1.448722	Prob. F(5,4540)		0.2034	No ARCH
		Obs*R-squared	7.241629	Prob. Chi-Square(5)		0.2033	
BSE Sensex	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000831	0.000158	5.244973	0.0000	
		α_0	2.49E-06	5.93E-07	4.201077	0.0000	
		α_1 (ARCH)	0.101278	0.013655	7.417158	0.0000	
		β (GARCH)	0.888847	0.012901	68.89965	0.0000	
	ARCH-LM Test	F-statistic	1.646870	Prob. F(5,4541)		0.1440	No ARCH
		Obs*R-squared	8.230303	Prob. Chi-Square(5)		0.1440	

: all ARCH & GARCH parameters are statistically significant at 1% level

T-GARCH (1,1) Model:

Threshold GARCH model is estimated in order to capture the leverage effect in selected five sectoral indices and BSE Sensex. T-GARCH is an asymmetric model. The estimated model results along with ARCH –LM test results are reported in Table 5.

Table 5: T-GARCH (1,1) Model Results

Sectoral Index	Equation/Test	Variable	Coefficient	Std. Error	z-Statistic	Prob.#	Inference
FMCG	Mean Variance	δ	0.000534	0.000169	3.169943	0.0015	
		α_0	8.08E-06	7.59E-07	10.64424	0.0000	
		α_1 (ARCH)	0.077424	0.009093	8.514958	0.0000	
		γ (leverage)	0.070489	0.010340	6.816960	0.0000	
		β (GARCH)	0.841358	0.009118	92.27492	0.0000	
	ARCH-LM Test	F-statistic	1.184103	Prob. F(5,4540)		0.3142	No ARCH
		Obs*R-squared	5.920619	Prob. Chi-Square(5)		0.3140	

Sectoral Index	Equation/Test	Variable	Coefficient	Std. Error	z-Statistic	Prob.#	Inference
I & T	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000766	0.000227	3.374811	0.0007	
		α_0	1.01E-05	6.79E-07	14.87419	0.0000	
		α_1 (ARCH)	0.084100	0.007126	11.80161	0.0000	
		γ (leverage)	0.080296	0.009219	8.710261	0.0000	
		β (GARCH)	0.856178	0.006318	135.5076	0.0000	
	ARCH-LM Test	F-statistic	0.984272	Prob. F(5,4540)		0.4257	No ARCH
		Obs*R-squared	4.922529	Prob. Chi-Square(5)		0.4254	
Auto	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000854	0.000188	4.546013	0.0000	
		α_0	8.97E-06	2.12E-06	4.234052	0.0000	
		α_1 (ARCH)	0.072630	0.016824	4.316955	0.0000	
		γ (leverage)	0.079962	0.029586	2.702729	0.0069	
		β (GARCH)	0.847111	0.023436	36.14576	0.0000	
	ARCH-LM Test	F-statistic	1.294144	Prob. F(5,4540)		0.2633	No ARCH
		Obs*R-squared	6.470052	Prob. Chi-Square(5)		0.2631	
Health care	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000638	0.000156	4.075322	0.0000	
		α_0	8.38E-06	8.60E-07	9.748414	0.0000	
		α_1 (ARCH)	0.106673	0.010837	9.843221	0.0000	
		γ (leverage)	0.043199	0.010240	4.218513	0.0000	
		β (GARCH)	0.817813	0.011763	69.52659	0.0000	
	ARCH-LM Test	F-statistic	1.542614	Prob. F(5,4540)		0.1730	No ARCH
		Obs*R-squared	7.710166	Prob. Chi-Square(5)		0.1729	
Oil & Gas	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000536	0.000210	2.548372	0.0108	
		α_0	4.47E-06	5.70E-07	7.842691	0.0000	
		α_1 (ARCH)	0.077105	0.006225	12.38562	0.0000	
		γ (leverage)	0.021715	0.006315	3.438582	0.0006	
		β (GARCH)	0.899653	0.005010	179.5632	0.0000	
	ARCH-LM Test	F-statistic	1.123967	Prob. F(5,4540)		0.3452	No ARCH
		Obs*R-squared	5.620305	Prob. Chi-Square(5)		0.3449	
BSE Sensex	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000561	0.000162	3.463693	0.0005	
		α_0	3.13E-06	6.51E-07	4.802517	0.0000	
		α_1 (ARCH)	0.047069	0.019281	2.441265	0.0146	
		γ (leverage)	0.101881	0.023047	4.420623	0.0000	
		β (GARCH)	0.885976	0.011985	73.92464	0.0000	
	ARCH-LM Test	F-statistic	0.757460	Prob. F(5,4541)		0.5805	No ARCH
		Obs*R-squared	3.789142	Prob. Chi-Square(5)		0.5802	

: All the ARCH & GARCH terms, constants and leverage effects are statistically significant

It is noticeable from the Table 5 that all the ARCH coefficients (α_1) are having positive sign and statistically significant implying that the news about previous period volatility is impacting significantly the volatility in the current period. The GARCH coefficients (β) are also having positive sign and statistically significant in all the five sectoral indices and in case of Sensex suggesting that the previous period's volatility impacting current period's conditional variance significantly. The sums of β and α_1 are less than 1 in all the five sectoral indices and for Sensex specifying that the volatility decays over a period of time. The sum of ARCH and GARCH coefficient is highest for daily returns of Oil & Gas (0.976758) followed by I & T (0.940278), Sensex (0.933045), Health care (0.924486), Auto (0.919741), FMCG (0.918782). Volatility persistence behaviour more pronounced in case of Oil & Gas and I&T compared to other sectors of BSE. The leverage effects are shown by the coefficient γ which is positive and statistically significant at 1% level in case of all the five sectoral indices

and for Sensex, suggesting that the bad news have greater influence on volatility than good news. Among sectoral indices the value of the coefficient of leverage effect is highest for I&T followed by Auto sector, FMCG, Health care and Oil & Gas sector. The value for BSE Sensex is 0.101881. The model diagnostic check done with the help of ARCH-LM test indicated absence of Heteroscedasticity in the residuals of all the six indices denoting that the fitted models are adequate technically.

E-GARCH Model:

The results of Exponential GARCH models are shown in the Table 6. In this case also all the ARCH (α_1) coefficients are having expected positive sign and statistically significant for all the selected six indices specifying that news about previous period's volatility influences the current period conditional variance significantly and positively in case of all the indices. Similarly all the GARCH (β) coefficients are also positive and statistically significant for all the five sectoral indices and BSE Sensex suggesting the volatility clustering and that the previous period's conditional variance influences the current period's conditional variance positively and significantly. The leverage effects given by γ are all negative and statistically significant specifying that negative shocks have greater impact on the current period's conditional variance than the positive shocks in case of all the six indices. The ARCH- LM tests conducted for testing the presence of heteroscedasticity show that the probability is higher than 0.05 revealing the absence of ARCH effect in the residuals of the estimated E- GARCH models hence, it may be inferred that the estimated models fitted well to the data.

Table 6: E-GARCH (1,1) Model Results

Sectoral Index	Equation/Test	Variable	Coefficient	Std. Error	z-Statistic	Prob.#	Inference
FMCG	Mean Variance	δ	0.000490	0.000162	3.029606	0.0024	
		α_0	-0.525634	0.039056	-13.45836	0.0000	
		α_1 (ARCH)	0.206582	0.011214	18.42108	0.0000	
		γ (leverage)	-0.052153	0.005968	-8.738268	0.0000	
		β (GARCH)	0.957908	0.003999	239.5138	0.0000	
	ARCH-LM Test	F-statistic	1.627503	Prob. F(13,4524)		0.0703	No ARCH
		Obs*R-squared	21.12422	Prob. Chi-Square(13)		0.0705	
I & T	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000781	0.000210	3.727361	0.0002	
		α_0	-0.258534	0.014901	-17.35069	0.0000	
		α_1 (ARCH)	0.161605	0.006672	24.21964	0.0000	
		γ (leverage)	-0.047575	0.004960	-9.592461	0.0000	
		β (GARCH)	0.982811	0.001483	662.5370	0.0000	
	ARCH-LM Test	F-statistic	1.238431	Prob. F(5,4540)		0.2882	No ARCH
		Obs*R-squared	6.191892	Prob. Chi-Square(5)		0.2880	
Auto	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000773	0.000185	4.174128	0.0000	
		α_0	-0.537051	0.098520	-5.451164	0.0000	
		α_1 (ARCH)	0.219155	0.029275	7.486073	0.0000	
		γ (leverage)	-0.061703	0.016980	-3.633797	0.0003	
		β (GARCH)	0.957061	0.009739	98.26949	0.0000	
	ARCH-LM Test	F-statistic	1.880365	Prob. F(6,4538)		0.0803	No ARCH
		Obs*R-squared	11.27157	Prob. Chi-Square(6)		0.0803	
Health care	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000601	0.000147	4.099848	0.0000	
		α_0	-0.536865	0.044628	-12.02984	0.0000	
		α_1 (ARCH)	0.221113	0.012412	17.81461	0.0000	
		γ (leverage)	-0.029762	0.005596	-5.317924	0.0000	
		β (GARCH)	0.958549	0.004493	213.3379	0.0000	
	ARCH-LM Test	F-statistic	1.461814	Prob. F(20,4510)		0.0839	No ARCH
		Obs*R-squared	29.18323	Prob. Chi-Square(20)		0.0842	

Oil & Gas	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000607	0.000200	3.036930	0.0024	
		α_0	-0.329028	0.023300	-14.12162	0.0000	
		α_1 (ARCH)	0.200154	0.008589	23.30370	0.0000	
		γ (leverage)	-0.021418	0.004528	-4.730652	0.0000	
		β (GARCH)	0.978744	0.002477	395.1896	0.0000	
	ARCH-LM Test	F-statistic	1.265433	Prob. F(8,4534)		0.2568	No ARCH
BSE Sensex	Mean Variance	Variable	Coefficient	Std. Error	z-Statistic	Prob.	
		δ	0.000472	0.000166	2.845528	0.0044	
		α_0	-0.363305	0.048782	-7.447460	0.0000	
		α_1 (ARCH)	0.202047	0.026307	7.680253	0.0000	
		γ (leverage)	-0.076446	0.014518	-5.265689	0.0000	
		β (GARCH)	0.976358	0.004681	208.5794	0.0000	
	ARCH-LM Test	F-statistic	1.240805	Prob. F(5,4541)		0.2871	No ARCH
		Obs*R-squared	6.203746	Prob. Chi-Square(5)		0.2869	

: All the ARCH & GARCH terms, constants and leverage effects are statistically significant

CONCLUSIONS AND RECOMMENDATIONS:

In the present paper volatility persistence and volatility clustering behaviour and leverage effect of the daily returns of the five sectoral indices of BSE Sensex mainly FMCG, I&T, Auto, Health care, Oil & Gas along with BSE Sensex have been analysed with the help of GARCH analysis. Both symmetric GARCH (1,1) and asymmetric GARCH models like T-GARCH (1,1) and E-GARCH (1,1) have been used for the analysis. The results indicated that all ARCH and GARCH estimated coefficients have expected sign and statistically significant in all the asymmetric and symmetric GARCH models thus suggesting that the news about the volatility in the previous period and lagged conditional variance impact significantly the volatility of the daily return series in the current period (of the five sectoral indices and BSE Sensex). The leverage effect is captured by the coefficient γ in both asymmetric models T-GARCH and E-GARCH have expected sign and significant showing that bad news impact significantly the current volatility than the good news of the same magnitude. Oil & Gas and I & T sectors have shown more volatility persistence behaviour and slower decay of volatility compared to the Auto, FMCG and Health care. Hence, risk avert investors may invest in Auto, FMCG and Health care sectors compared to other two sectors. And investors who are interested in more returns (risk lovers) may invest in Oil & Gas and I&T as more risk (volatility) normally may result into more returns. Investors are also required to be vigilant about the positive and negative shocks that enter the BSE stock market as the results showed that these shocks impact the selected sectoral indices significantly. This watchfulness might help the investors to take appropriate investment decisions at the right time to avoid the losses. The government and regulatory bodies of stock markets also need to take necessary steps to avoid the high volatility behaviour of the stock indices in Bombay Stock Exchange (as evidenced by the results) in order to protect the interest of the foreign and domestic investors.

LIMITATIONS OF THE STUDY:

The present study is restricted to the analysis of volatility behaviour and leverage effect among the five sectors of the BSE along with the Sensex. Further research may be required to understand the causes of volatility with the help of techniques like Cointegration and Error Correction Models. This kind of analysis may give a better understanding of the Stock markets' functioning and enable the investors and regulatory authorities in understanding the movements of different stock indices of BSE.

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