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ANALYSIS OF STOCK MARKET VOLATILITY IN INDIAUSING GARCH MODELS

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ABSTRACT

The present paper made an attempt to model the volatility (conditional variance) in the daily returns of the S&P BSE Sensex for the period January 2015 to February 2018 with the help of General Auto Regressive Conditional Heteroskedasticity Models. Specially GARCH (1,1) model is used to capture the volatility present in the daily returns of Senex. The results show that estimated coefficients of ARCH and GARCH are highly significant and having expected sign thus validating the presence of the persistent volatility clustering though, conditional variance is showing mean reverting process as the sum of the ARCH and GARCH coefficients is less than one. The current volatility in the daily returns of the Sensex closing prices are significantly influenced by the previous period's news about the volatility and lagged volatility. The results confirm the high and persistent volatility in BSE Sensex daily returns which may be discouraging for the investors to invest in Sensex and this may be an indication to the policy makers and stock regulators to take appropriate actions.

Key words: Volatility, Stock Market, ARCH, GARCH, Returns

INTRODUCTION

Stock markets play very important role in the economy of a country. The growth and progress of industry and commerce of country is heavily influenced by the stock market as it is avital source of capital to them. All the economic activities of these sectors be it expansion of existing business or establishing a new venture, depend on stock markets for required finance asstock market is the primary source of funds to these activities. Stock markets also provide ample opportunities for investors to invest their money. Hence, fluctuations in stock markets are very keenly observed by various stake holders mainly, investors, industry, government and central bank of a country. The stock markets of a country are characterised by high volatility due to the influence of multiplicity of variables operating in the economic system of a country and in the world economy. This volatility in turn influences the activities of different stakeholders of the stock market. Indian stock markets are also highly volatile resulting into lot of fluctuations in the stock prices which create lot of uncertainties and risks in returns to different players in the market. Hence, it becomes important to model the volatility of financial time series over a period of time. Higher volatility means larger fluctuations in security values and lower volatility means less variation in security values. Experts have developed various econometric models to estimate the volatility of financial instruments. Among theseAuto Regressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) and Generalised Auto Regressive Conditional Heteroskedasticity (GARCH) proposed by Bollerslev (1986) and Taylor (1986) have become very popular in modelling stock market volatility. The presents study aims at modelling the volatility in the daily returns of the S&P BSE Sensex with the help of GARCH model. This BSE Sensex also known as Sensex plays a very important role in the domestic stock markets of India.

LITERATURE REVIEW

The rich literature is available on modelling of the stock market volatility. Number of studies have used GARCH models specifically to capture the volatility of stock markets in different countries of the world. Some of the relevant studies discussed here gave the required theoretical framework for the present analysis. Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models were used to estimate the volatility in the daily returns of the main stock market of Sudan specifically, Khartoum Stock Exchange for a period from January 2006 to November 2010 and results clearly indicated that the conditional variance was highly persistent with explosive process (Ahmed &Suliman, 2011). The results further indicated that asymmetric models provided the better results comparted to symmetric models. Another study modelled the Indian stock market volatility using both asymmetric and symmetric GARCH models and results showed that there was no positive relationship between the increased risk and increased return (Banumathy&Azhagaiah, 2015).Nigerian Stock Market Return Volatility was modelled employing symmetric and asymmetric GARCH models and based on the results it was concluded that there was high persistent volatility for the NSE return series and no asymmetric shock phenomena observed in the series (Adesina, 2013). Nairobi Securities Stock Market was analysed on the basis of GARCH models and results supported the positive relationship between the volatility and expected stock returns (Maqsood, et al. 2017).A study aimed at identifying the relationship between returns and volatility among South Africa and China using GARCH models concluded that there existed enough evidence of high volatility in both the markets (Cheteni, 2017). Similar kind of study made in Sudan and Egypt stock markets evidenced explosive and persistent process of conditional variance among return series respectively (Zakaria, et.al., 2012). Jordan Sock Market volatility study based on the family of GARCH models showed that there existed volatility clustering in return series but EGARCH output did not support the presence of leverage effect (Najjar, 2016). The literature review provided the required theoretical ground for analysing the volatility of the BSE Sensex return series in India with the help of GARCH models. The following section presents the theoretical framework adopted in the present analysis.

RESEARCH METHODOLOGY

Data

The study depends on the secondary data collected from the finance.yahoo.com- web site. The S&P BSE Sensex closing prices have been used to represent the Indian stock market. The daily closing prices of BSE Sensex were collected for a period of 3 years from 2nd January 2015 to 14th February 2018 excluding public holidays resulting into 787 observations. The E-view 9 econometrics software was used for the data analysis.

Theoretical framework

Data Transformation

The daily closing prices of BSE Sensex were converted into daily returns with the help of the following equation

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

Where $R_t = logarithmic\ daily\ returns\ on\ BSE\ Sensex\ for\ time\ t$

$P_t = Clsoing\ price\ at\ time\ t$; $P_{t-1} = closing\ price\ at\ time\ t-1$

Descriptive Statistics

To know the distributional properties of the daily return series of the BSE Sensex various descriptive statistics like Mean, Median, Standard Deviation, Skewness, Kurtosis and Jarque-Bera Statistics have been calculated for the return series.Graphs like Quantile-Quantile (Q-Q) plot also used to test for normality of the returns series under consideration (Wilk &Gnanadesikan, 1968).

Stationarity Tests

It is necessary to identify whether the return series under considerations are stationary or not before proceeding to further analysis. This is done with the help of Augmented Dicky Fuller (1979) and Phillips – Perron(1988)tests. The series have to be stationary for further analysis of the data. Along with these tests corrrelogram of the squared residuals and Ljung-Box (Q) statistics are also embraced to test the correlation in residuals (Adesina, 2013).

Heteroscedasticity Test

Next step is to test for the presence of heteroscedasticity (Auto Regressive Conditional Heteroscedasticity – ARCH effects) in residuals which were obtained from regressing the conditional mean equation of ARMA (1,1) process as given below

$R_t = \emptyset_1 R_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$ ------------------ (2)

The Lagrange Multiplier (LM) test proposed by Engel (1982) is employed to test for ARCH effects in residuals obtained from equation (2) above. The following equation is run to test for the ARCH effects among the residuals (e_t)

$e_t^2 = \delta_0 + \delta_1 e_{t-1}^2 + \delta_2 e_{t-2}^2 + \dots\dots\dots\dots\dots.. + \delta_p e_{t-p}^2 + \epsilon_t$ ------------- (3)

Volatility Measuring Model $[\boldsymbol{GARCH}\ (\mathbf{1},\mathbf{1})]$

Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) is the technique that is very popular and employed by researchers in modelling the conditional volatility (symmetric). The GRACH technique adopted to measure the volatility in daily returns of the series is described below. The GARCH model involves the combined estimation of two equation mainly mean equation and conditional variance equation (Bollerslev, 1986; Taylor, 1986) as specified below

$R_t = \mu + \varepsilon_t$; Mean Equation-------------------------------- (4)

Where $R_t = return\ at\ time\ 't';\ \mu = mean\ return\ ;\ \varepsilon_t = residual\ return\ at\ time\ 't'$

$\sigma_t^2 = \gamma + \propto \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$; Variance Equation ------------------ (5)

Where, $\gamma > 0 ; \propto \geq 0 ;\ \beta \geq 0$

$\sigma_t^2 =$ Conditional variance at time $'t'$;

ε_{t-1}^2 = squared error term at time $'t-1'$(ARCH term)

σ_{t-1}^2 = conditional *variance at time* $'t-1'$ (GARCH term)

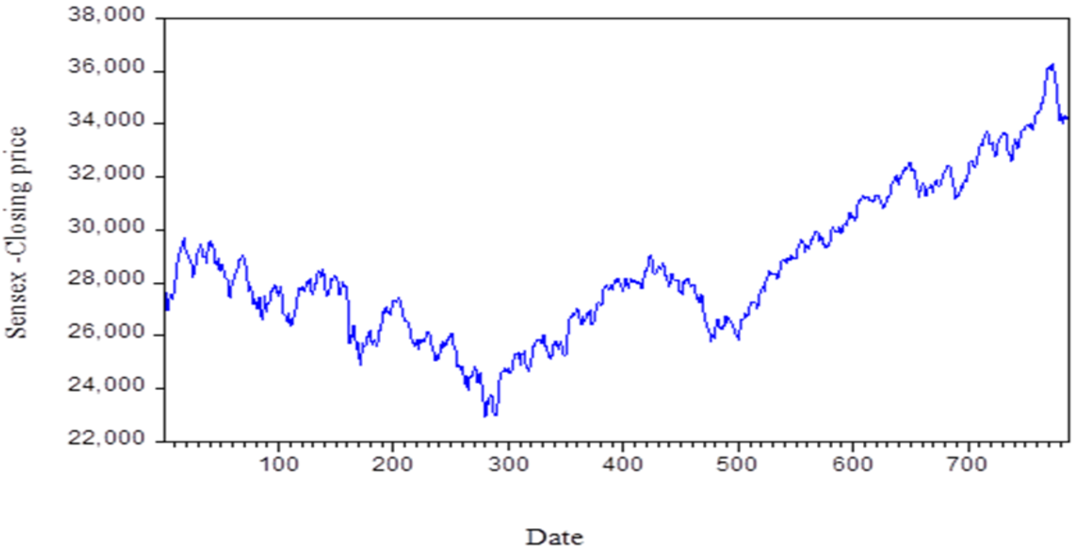
$\propto$ = ARCH parameter : β = GARCH parameter

RESULTS AND DISCUSSIONS

Data Transformation

In this section the results of the data analysis are presented and discussed. The closing prices of BSE Sensex for the study period have been plotted in Figure 1 below.

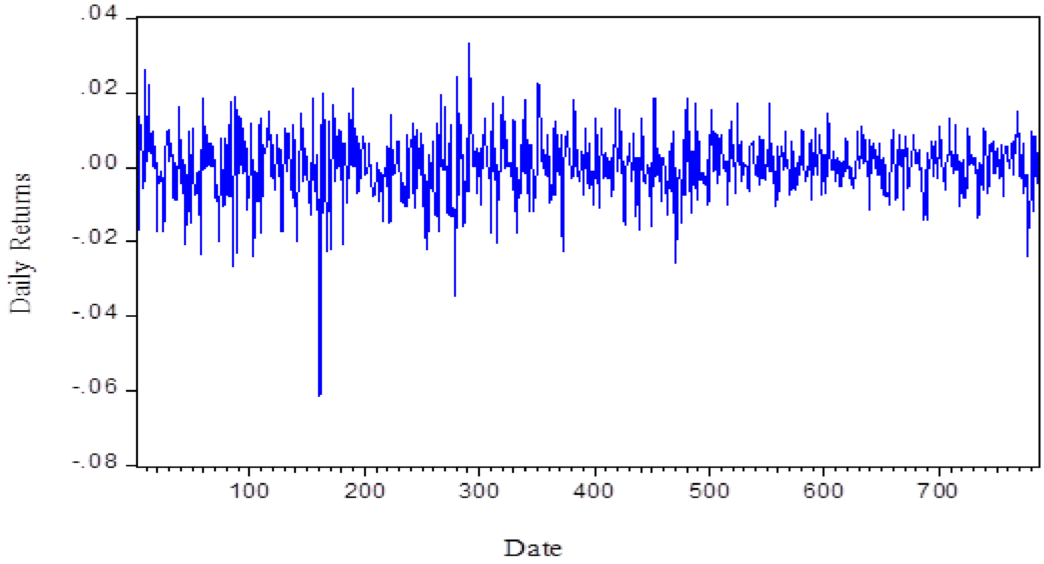
Figure 1: Line Graph of Daily Closing Prices of BSE Sensex (02-01-2015 to 14-02-2018)



Source: Data Analysis

It is clear from the Figure 1 that the Sensex daily closing prices show lot of volatility during the study period. The series are non-stationary. Hence, to make series stationary which is the pre-requisite for the further analysis, closing prices are converted into daily returns (logarithmic) series and the plot of the return series are shown in Figure 2.

Figure 2: Graph of Daily Returns of BSE Sensex – Volatility Clustering



Source: Data Analysis

The observation of the Figure 2 reflects the evidence of Volatility Clustering of daily returns of the BSE Sensex. The periods of low volatility persist for a longer period followed by the sustained high volatility period resulting into volatility clustering. But the series fluctuate around the mean return but the variance is time varying.

Summary Statistics

The descriptive statistics of the daily returns are presented in Table 1.

Table 1: Descriptive Statistics of Daily Returns

Mean	0.000266
Median	0.000000
Maximum	0.033236
Minimum	-0.061197
Std. Dev.	0.008534
Skewness	-0.675641
Kurtosis	7.245295
Jarque-Bera	649.2111
Probability	0.000000

Source: Data Analysis

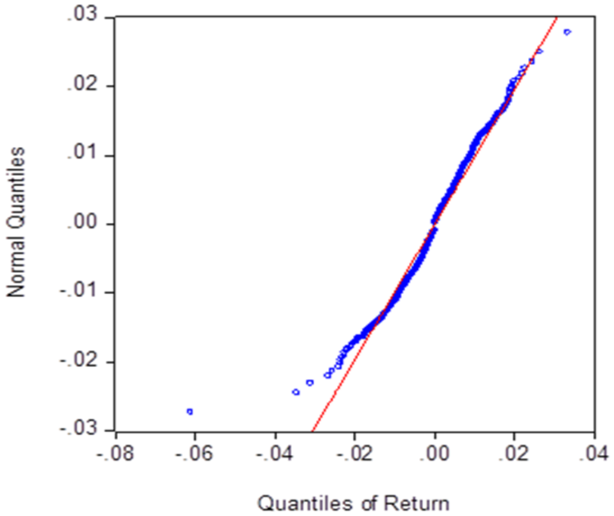
The range for series is -0.061197to 0.033236 with mean return of 0.000266 and the standard deviation of 0.008534. The Skewness is having negative value indicating that the return series have a long-left tail. The value of Kurtosis being greater than 3 around 7.245295 showing leptokurtic distribution of the series under consideration. Based on the values of

Skewness and Kurtosis it may be inferred that the return series are not normally distributed. This is further validated by the Jarque-Bera test statistics whose probability is < 0.01 specifying that the series are not confirmed to Normal Distribution.

Quantile-Quantile (Q-Q) Plot

The Quantile-Quantile (Q-Q) plot is also presented in Figure 3 below to check the distribution of daily return series.

Figure 3: Quantile-Quantile plot for the Daily Returns



Source: Data Analysis

If the series are normally distributed then the Q-Q plot will lie on a line otherwise it will deviate from the straight line representing s-shape (Adesina, 2013). It may be seen from the Figure 3 that the return series under consideration are not normally distributed as the plot does not indicate the straight line.

Stationarity Test Results

The transformed series i.e., daily returns series are tested for stationarity and the results of the same are reported in Table 2. The ADF and P-P test statistics are much higher than the test critical values and probability is <0.01 indicating that the null hypothesis of unit root is rejected and it is concluded that the daily return series are stationary at levels for the study period.

Table 2: Stationarity Test Results for Daily Returns

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-26.66662	0.0000
Test critical values:	1% level		-3.438465	
	5% level		-2.865012	
	10% level		-2.568674	
Phillips-Perron test statistic			-26.64706	0.0000
Test critical values:	1% level		-3.438465	
	5% level		-2.865012	
	10% level		-2.568674	
*MacKinnon (1996) one-sided p-values.				

Source: Data Analysis

Results of Heteroskedasticity (ARCH) test

To test the presence of ARCH effects in residuals of BSE daily return series firstly the equation (1) was run to get the residuals and then the Lagrange Multiplier (LM) test was applied to test the null hypothesisH_0

$$\delta_0 = \delta_1 = \delta_2 = \ldots\ldots\ldots\ldots\ldots.. \delta_p = 0 \text{ ; No ARCH effect}$$

Against alternative hypothesis H_1

$\delta_0 \neq 0, \delta_1 \neq 0, \delta_2 \neq 0 \ldots\ldots\ldots\ldots\ldots.. \delta_p \neq 0$; There is ARCH effect

The results of the LM tests are presented in Table 3. The test results clearly show that F-statistics is high and probability is < 0.05 indicating the rejection of null hypothesis at 5% level of significance thus emphasising that there exists ARCH effects in the residuals of daily returns series. This is further tested with the help of the correlogram of the squared residuals and Ljung-Box Q-statistics shown in Figure 4.In Figure 4 allthe autocorrelations and partial auto correlations are insignificant except first one implying the presence of ARCH effect as the Q-statistics probability is < 0.05. The presence of ARCH effect is necessary for applying the GARCH models this leads us to next step of the analysis that is modelling volatility with the help of GARCH technique.

Table 3: ARCH-LM Test for Heteroscedasticity (Daily Returns)

F-statistic	**2.720212**	**Prob. F (5,774)**		**0.0190**
Obs*R-squared	**13.46980**	**Prob. Chi-Square (5)**		**0.0194**
Dependent Variable: RESID^2				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	5.83E-05	8.16E-06	7.150847	0.0000
RESID^2(-1)	0.010727	0.035936	0.298511	0.7654
RESID^2(-2)	0.097003	0.035934	2.699474	0.0071
RESID^2(-3)	0.084375	0.035984	2.344812	0.0193
RESID^2(-4)	0.009791	0.035933	0.272491	0.7853
RESID^2(-5)	-0.019758	0.035365	-0.558693	0.5765
R-squared	0.017269			
Adjusted R-squared	0.010921			
S.E. of regression	0.000177	Akaike info criterion		-14.43370
Sum squared resid	2.42E-05	Schwarz criterion		-14.39786
Log likelihood	5635.143	Hannan-Quinn criter.		-14.41991
F-statistic	2.720212	Durbin-Watson stat		1.994695
Prob(F-statistic)	0.019048			

Source: Data Analysis

Figure 4: Correlogram of the Squared Residuals (Daily Returns)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.018	0.018	0.2596	0.610
		2	0.098	0.098	7.8405	0.020
		3	0.082	0.080	13.183	0.004
		4	0.019	0.008	13.470	0.009
		5	-0.003	-0.019	13.477	0.019
		6	0.137	0.130	28.404	0.000
		7	0.024	0.022	28.855	0.000
		8	0.029	0.005	29.533	0.000

Source: Data Analysis

GARCH (1,1) Results

Once it is confirmed from the above results that there exists ARCH effect in residuals of the daily return series the further analysis was done by applying the GARCH (1,1) model and the results of GARCH are shown in Table 4. The results reveal that the mean return (μ) in mean equation is significant at 10% level. In Variance equation constant (γ), Conditional Variance coefficients of ARCH ($\propto$) and GARCH (β) terms are significant at 1% level respectively as their corresponding probabilities are < 0.05. This indicates that the lagged conditional variance and lagged squared disturbance terms significantly impact the current volatility of daily returns of the BSE Sensex.

Table 4: GARCH (1,1) Results for Daily Returns

Mean Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
μ	0.000495*	0.000270	1.833437	0.0667
Variance Equation				
γ	1.37E-06***	5.39E-07	2.539938	0.0111
∝ (ARCH effect)	0.052582***	0.020618	2.550308	0.0108
β (GARCH effect	0.928236***	0.017626	52.66309	0.0000
$\propto +\beta$	0.980818			
R-squared	-0.000722	Mean dependent var		0.000266
Adjusted R-squared	-0.000722	S.D. dependent var		0.008534
S.E. of regression	0.008537	Akaike info criterion		-6.759759
Sum squared resid	0.057138	Schwarz criterion		-6.735985
Log likelihood	2657.206	Hannan-Quinn criter.		-6.750618
Durbin-Watson stat	1.868898			

***,* : indicate significant at 1% and 10% level respectively ; Source: Data Analysis

The estimated GARCH coefficient (0.928236) is larger than the ARCH coefficient (0.052582) in conditional variance equation. This implies that the volatility is more sensitive to previous period's volatilities compared to the news about volatility from the previous periods. The sum ofthe ARCH and GARCH coefficients ($\propto + \beta = 0.980818$) which shows volatility persistence behaviour is < 1 implying the presence of mean reverting variance process in daily returns (Ahmed & Suliman, 2011).Since the sum of ARCH and GARCH terms are close to 1 suggesting that though the shocks decay with time but may persist for many periods in future.To test the estimated GARCH model is well specified or not ARCH-LM test is used to check the presence of ARCH effect in residuals and the results of the tests are shown in Table 5.

Table 5 : ARCH –LM Test for Heteroscedasticity for Residuals GARCH (1,1)

F-statistic	**0.586970**	**Prob. F(5,774)**		**0.7100**
Obs*R-squared	**2.946427**	**Prob. Chi-Square(5)**		**0.7082**
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.060504	0.117109	9.055691	0.0000
WGT_RESID^2(-1)	-0.032289	0.035908	-0.899238	0.3688
WGT_RESID^2(-2)	0.024077	0.035924	0.670236	0.5029
WGT_RESID^2(-3)	-0.006671	0.035936	-0.185648	0.8528
WGT_RESID^2(-4)	-0.009248	0.035923	-0.257436	0.7969
WGT_RESID^2(-5)	-0.044542	0.035896	-1.240865	0.2150
R-squared	0.003777			
Adjusted R-squared	-0.002658			
S.E. of regression	2.364829	Akaike info criterion		4.566951
Sum squared resid	4328.530	Schwarz criterion		4.602792
Log likelihood	-1775.111	Hannan-Quinn criter.		4.580736
F-statistic	0.586970	Durbin-Watson stat		1.995154
Prob(F-statistic)	0.710011			

Source: Data Analysis

It may be inferred from LM test results (Table 5) that there is no ARCH effect left in the residuals as the F-probability is very high >0.05 indicating the inability to reject the null hypothesis of no ARCH effect.So, there is no ARCH effect remaining in the residuals hence, the model specification is reasonably good. This is further substantiated by the correlogram of the squared residuals presented in Figure 5.

Figure 5: Correlogram of Squared Residuals (GARCH (1.1) Model)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.033	-0.033	0.8487	0.357
		2	0.026	0.025	1.3649	0.505
		3	-0.009	-0.008	1.4329	0.698
		4	-0.007	-0.008	1.4721	0.832
		5	-0.044	-0.045	3.0316	0.695
		6	0.057	0.055	5.6322	0.466
		7	-0.034	-0.029	6.5595	0.476
		8	0.002	-0.003	6.5637	0.584

Source: Data Analysis

None of the Auto Correlations (AC) and Partial Auto Correlations (PAC) are significant as the Q-statistics Probability for all the ACs and PACs are high and > 0.05 indicating absence of any correlation between the squared residuals and the absence of ARCH effect. Therefore,it may be concluded that the variance equation is well specified.

CONCLUSION

In the present paper an attempt has been made to model the presence of volatility in daily return series of BSE Sensex for the period of three years (Jan 2015 to Feb 2018) using GARCH (1,1) model. The estimated coefficient of ARCH is having expected positive sign and significant at 1% level showing that the news about lagged volatility significantly impact the current volatility and GARCHcoefficient is also positive and significant at 1% revealing that the previous period's volatility influences greatly the current volatility of the daily returns of the BSE Sensex. The sum of ARCH and GARCH coefficients is less than one signalling mean reversing process of the series but the value is near to one suggesting the presence of Volatility Clustering and persistence of volatility in daily returns of BSE Sensex. The presence of high volatility in the daily market returns may discourage the investors to invest in BSE Sensex.

Therefore, present study results may be of help to policy makers and regulators of stock market.

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