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A Study on Volatility Modelling of BSE Sensex

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Abstract

The present study has analysed the volatility in the returns of BSE Sensex for the period April 2003-March 2012. It is found that the time series data is stationary but not normally distributed. The return series is serially correlated and thus there is autocorrelation. GARCH (1,1) model is used to study the conditional variances and it is found to be a good fit model as the coefficient value is close to one. This shows that a positive/negative return leads future forecasts of the variance to high/low for a long period of time. TARCH (1,1) model is applied to analyse the leverage effect. The results show the presence of leverage effect and there is also news asymmetry in the market thereby concluding that bad news has more effect on the volatility than the good news.

Keyword: Volatility, Autocorrelation, GARCH, TARCH, Leverage effect

Introduction

Volatility is the most basic statistical risk measure.It can be used to measure the market risk of a single instrument or an entire portfolio ofinstruments. While volatility can be expressed in differentways, statistically, volatility of a random variableis its standard deviation. In day-to-day practice, volatilityis calculated for all sorts of random financialvariables such as stock returns, interest rates, the marketvalue of a portfolio, etc. Stock return volatility measuresthe random variability of the stock returns. In simple words,stock return volatility is the variation of the stock returnsin time. More specifically, it is the standard deviationof daily stock returns around the mean value and thestock market volatility is the return volatility of theaggregate market portfolio.Volatility of stock returns has been mainly studiedin the developed economies. After the seminal work ofEngle (1982) on the Autoregressive Conditional Heteroscedasticity(ARCH) model and its generalized form(GARCH) by Bollerslev (1986), much of the empirical work has used these models and their extensions (seefor example, French, Schwert and Stambaugh, 1987; Akgiray, 1989; Connolly, 1989; Ballie and DeGennaro,1990; Lamoureux and Lastrapes, 1990; CorhayandTourani, 1994; Geyer, 1994; Nicholls and Tonuri, 1995;Booth, Martikainen and Tse, 1997; de Lima, 1998;and Sakata and White, 1998).

There is relatively less empirical research on stockreturn volatility in the emerging markets. In the Indian context, Roy and Karmakar (1995) focused on the measurementof the average level of volatility as the samplestandard deviation and examined whether volatility has increased in the early 1990s; Goyal (1995) used conditional volatility estimates as suggested by Schwert(1989)to study the nature and trend of stock return volatility and the impact of carry forward system on the level ofvolatility; Reddy (1997-98) analysed the effects of marketmicrostructure, e.g., establishment of the National StockExchange (NSE) and the introduction of Bombay Stock Exchange Online Trading (BOLT) system on the stock return volatility measured as the sample standard deviationof the closing prices; Kaur (2002) analysed theextent and pattern of stock return volatility during 1990-2000 and examined the effect of company size, day-ofthe-week, and FII investments on volatility measured asthe sample standard

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deviation.ARCH/GARCH models have been used by Thomas(1995, 1998), Pattanaik and Chatterjee (2000) and Kaur(2002) to model volatility in the Indian financial markets.Shenbagaraman(2003) examined the impact of introduction of index futures and options on the volatility of underlying stock index using a GARCH model. Kumar and Mukhopadhyay (2002) applied the GARCH modelsto examine the co-movement and volatility transmissionbetween the US and Indian stock markets.

Though, in most of the cases, the ARCH and theGARCH models are apparently successful in estimatingand forecasting the volatility of the financial time seriesdata, they cannot capture some of the important featuresof the data. The most interesting feature not addressedby these models is the 'leverage effect' where the conditional variance tends to respond asymmetrically topositive and negative shocks in errors. To solve thisproblem, many nonlinear extensions of the GARCH modelhave been proposed. Nelson (1991) proposed an exponentialGARCH (EGARCH) model based on a logarithmicexpression of the conditional variability in the variableunder analysis. Later, a number of modificationswere derived from this method. One of them is theThreshold ARCH (TARCH) method which was introduced by Zakoian(1994). The model developed byGlosten, Jagannathan and Runkle (GJR, 1993) has beenconsidered the best in estimating the impact of positiveand negative shocks on volatility (Engle and Victor, 1993).Curiously all these models have been developed andused on economic and financial data mostly taken fromthe developed countries. The ARCH and GARCH literatureon emerging markets is, however, scanty. Although,recently, a few studies have been carried out on emergingmarkets, surprisingly thereis no study that has estimated and forecasted conditionalvolatility using ARCH and GARCH methods on Indiandata. Hence, the present study has the following objectives-

- To study the nature of the distribution of data relating to market returns during the period of study.
- To analyse the presence of volatility clustering during the period of study.
- To explore the presence of leverage effect on the BSE during the period of study.

Literature Review

Batra (2004) applied GARCH model and examined time varying pattern of stock market volatility in India and observed that liberalisation of the market did not have any direct implications for the stock return volatility. Kaur (2004) reported significant correlation in daily returns of SENSEX and Nifty and found high volatility in the months of February and March. Karmakar (2005) found strong evidence of time varying volatility and low volatility clustering in the Indian Capital Market. Banerjee et al. (2006) investigated the presence of long term memory in the stock returns in India and reported long memory in its conditional variance. But, this study did not find the leverage effect. Joshi et al. (2008) successfully explored the movements of stock market volatility of BSE and NSE. Goudcarzi et al. (2011)studied the effects of good and bad news on the volatility of BSE 500 stock index during the financial crisis of 2008-2009 and concluded that the bad news in the Indian market increased volatility more than the good news by applying EGARCH and TGARCH models. SomSankar Sen et al. (2012)in their study found that the returns were serially correlated and volatility clustering was present during the period of study. Their results show that news asymmetry and leverage effect are present in the market.

Data and Methodology

The present study uses the daily returns of BSE SENSEX for the period 01-04-2003-03 to 04-02-2012. The daily closing sensex values are obtained from bseindia.com and the returns are calculated on the basis of the following-

If l_t be the closing level of Sensex on date t and l_{t-1} be the same for its previous business day, i.e., omitting intervening weekend or stock exchange holidays, then the one day return on the market portfolio is calculated as:

$$r_t = \ln \frac{l_t}{l_{t-1}} X\ 100$$

where, ln(z) is the natural logarithm of 'z.'

To test for structural breaks, Chow Test is applied to confirm whether structural breaks are present in the period or not. E Views 7 is used to calculate Chow test and results are interpreted.

Distribution of Data:

To analyse the pattern of distribution of data skeweness and kurtosis have been calculated. Zero skewness implies symmetry in the distribution whereas kurtosis indicates the extent to which probability is concentrated in the centre and especially at the tail of the distribution. Kurtosis measures the peakedness of a distribution relative to the normal distribution. A distribution with equal kurtosis as normal distribution is called 'mesokurtic'; a distribution with small tails is called 'platykurtic' and a distribution with a large tail is called 'leptokurtic'. Eviews 7 has been used to calculate skewness and kurtosis.

Leverage Effect

The time series data used in the study must be stationary. Mean, variance and co-variance of a stationary time series data does not change with the time sift. If the data is non-stationary then regression results using such data would be spurious. Augmented Dickey Fuller test (ADF) is used to test the stationarity of data.

Testing for ARCH Effects

Engle (1982) ARCH model is used to test for ARCH effects for the data considered for the study. For this the following AR (1) equation has been run-

$$y_t = \alpha + \beta y_{t-1} + \varepsilon_t \tag{1}$$

where y_t is the market return at day t.

A test for the presence of ARCH in the residuals has been calculated by regressing the squared residuals on a constant and p lags, here p has been taken as 1.

$$\hat{\varepsilon}_t^2 = \hat{a}_0 + \sum_{i=1}^{q} \hat{a}_i \hat{\varepsilon}_{t-i}^2 \tag{2}$$

The observed *R squared statistic is Engle's LM statistic, computed as the number of observations times from the test regression. If the F statistic and the LM-statistic are found significant then there is ARCH effect.

Testing for GARCH Effect:

In the present study, since there is no exogenous variable the above equation is represented as the AR(1) equation

$$y_t = \alpha + \beta y_{t-1} + \varepsilon_t$$

The conditional variance ε^2 can be stated in the following equation-

$$\sigma_t^2 = a + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

where,

ε_{t-1}^2 is the volatility from the previous period, measured as the lag of the squared residuals from the mean equation. It is also called the ARCH term.

ε_{t-1}^2 is the last period's forecast variance and it is also called GARCH term.

Testing for TARCH Effects

Glosten et al. (1993) introduced Threshold GARCH model (TARCH) which is also known as GJR model which is an extension of GARCH with an additional term to account for possible symmetries. The conditional variance is represented as follows-

$$\sigma_t^2 = a + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

where,

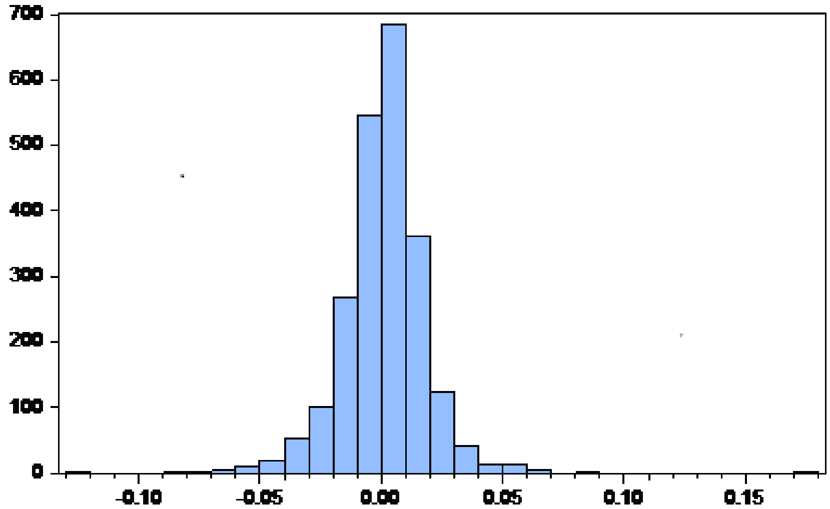
$$I_{t-1} = 1 \text{ if} < 0$$
$$= 0 \text{ otherwise no news}$$

In this model $\varepsilon_{t-1} > 0$ is good news and $\varepsilon_{t-1} < 0$ is bad news. They have differential effects on conditional variance. In practice, threshold values different from zero can be used as one would expect that only large shocks attract investors' attention.

Analysis and Interpretation

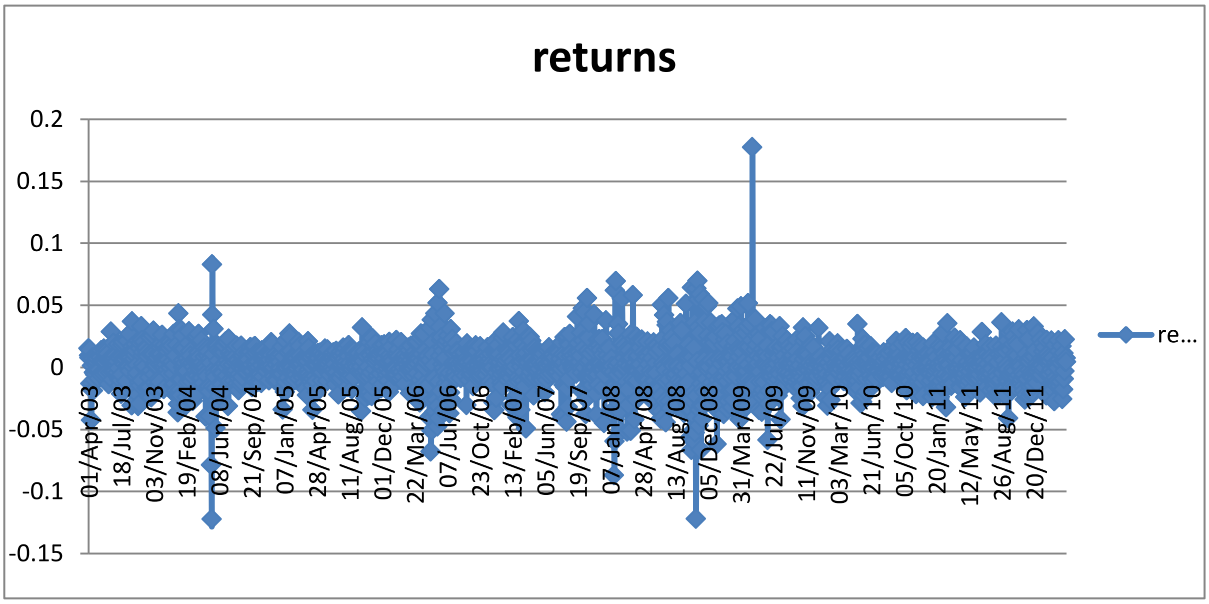
Table 1shows the descriptive statistics of Sensex returns for the period selected for the study. It can be seen that the returns vary from -0.12237 to 0.177441 thereby stating that there is wide fluctuation in the daily returns of the sensex. The mean return for the entire period is 0.000903 which is close to zero. Skewness is negative (-0.000118) indicating a relatively long left tail compared to the right one. Kurtosis (11.98497) which is in excess of 3 indicates heavy tails and the distribution is leptokurtic. The findings are similar to that of the existing literature and with a high Jarque-Bera statistic, it can be confirmed that the returns series is not normally distributed.

Table 1: Descriptive statistics of Sensex returns



Series: RETURNS	
Sample 4/01/2003 4/03/2012	
Observations 2250	
Mean	0.000903
Median	0.001554
Maximum	0.177441
Minimum	-0.122377
Std. Dev.	0.017152
Skewness	-0.000118
Kurtosis	11.98497
Jarque-Bera	7568.403
Probability	0.000000

Figure 1: Sensex Daily Returns



The graphical representation of the Sensex daily returns is depicted in Fig.1. The figure indicates that there is volatility clustering. Clusters could be found in the periods viz., April 2003-Jan 2004, Aug 2004-June2005, July 2006-May 2007 and so on. There are also periods where volatility is comparatively more such as May 2004, Sep 2008, May 2009.

Table 2: Results of Chow Breakpoint test

Chow Breakpoint Test: 1/02/2012
Null Hypothesis: No breaks at specified breakpoints
Equation Sample: 1/4/2003 3/4/2012

F-statistic	0.783388	Prob. F(2,2245)	0.4570
Log likelihood ratio	1.569021	Prob. Chi-Square(2)	0.4563
Wald Statistic	1.745339	Prob. Chi-Square(2)	0.4178

Table 2 shows the results of Chow Breakpoint test. It can be inferred from the table that the calculated F statistic 0.783388 is not significant @5% and thereby it confirms that there is no structural breaks in the data period and the null hypothesis that 'No breaks at specified points' is accepted.

Table 3: Correlogram Analysis

Lags	AC	PAC	Q –Stat.	Prob.
1	–0.444	–0.444	443.70	0.000
2	–0.075	–0.339	456.45	0.000
3	0.013	–0.257	456.80	0.000
4	0.026	–0.176	458.29	0.000
5	–0.006	–0.134	458.37	0.000
6	–0.050	–0.179	464.01	0.000
7	0.020	–0.170	464.89	0.000
8	0.036	–0.118	467.77	0.000
9	–0.025	–0.122	469.15	0.000
10	0.028	–0.065	470.87	0.000
11	–0.026	–0.077	472.45	0.000
12	–0.015	–0.106	472.93	0.000
13	0.008	–0.113	473.09	0.000
14	0.039	–0.051	476.61	0.000
15	–0.032	–0.062	478.92	0.000
16	–0.019	–0.089	479.72	0.000
17	0.061	–0.012	488.14	0.000
18	–0.049	–0.054	493.69	0.000
19	0.038	0.010	496.90	0.000
20	–0.056	–0.048	504.12	0.000
21	0.031	–0.034	506.30	0.000
22	0.017	–0.006	506.98	0.000
23	–0.054	–0.070	513.66	0.000
24	0.037	–0.055	516.78	0.000
25	0.002	–0.050	516.80	0.000
26	0.004	–0.035	516.83	0.000
27	–0.009	–0.043	517.02	0.000
28	0.021	0.003	518.06	0.000
29	–0.019	–0.009	518.86	0.000
30	–0.006	–0.010	518.95	0.000
31	–0.005	–0.029	519.02	0.000
32	0.009	–0.030	519.20	0.000
33	–0.006	–0.040	519.28	0.000
34	0.027	0.001	520.90	0.000
35	–0.031	–0.029	523.06	0.000
36	0.017	–0.021	523.75	0.000

Contd...

Table 3reports the results of auto correlation and the results of *Q* statistic. It could be seen that the *Q* statistic at each lag is highly significant and therefore there is significant auto correlation in the daily squared returns and hence volatility clustering is present for the period selected for the study. Fama's (1965) also observed that stock returns exhibit volatility clustering where large returns tend to be followed by large returns and small returns by small returns leading to contiguous periods of volatility and stability.

Table 4: Unit Root Test

Variable Name	Computed ADF (t statistic)
Returns	–44.50944*

*Significant @ 1%

Table 4shows the results of Unit Root tests. Augmented-Dickey Fuller (ADF) tests are reported and the calculated value of ADF is -44.50944. This is significant @ 1% and hence it can be concluded that the variable 'Returns' is stationary at this level.

Table 5: Results of ARCH Effect

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 4/02/2003 4/03/2012
Included observations: 2249 after adjustments
Convergence achieved after 21 iterations

Contd...

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001114	0.000308	3.618495	0.0003
RETURNS(–1)	0.036391	0.016142	2.254410	0.0242
Variance Equation				
C	0.000186	4.99E-06	37.38435	0.0000
$RESID(-1)^2$	0.394823	0.020571	19.19348	0.0000
R-squared	0.003051	Mean dependent var		0.000896
Adjusted R-squared	0.002607	S.D. dependent var		0.017153
S.E. of regression	0.017131	Akaike info criterion		–5.422241
Sum squared resid	0.659396	Schwarz criterion		–5.412071
Log likelihood	6101.310	Hannan-Quinn criter.		–5.418529
Durbin-Watson stat	1.943089			

Table 6: ARCH-LM Results

Heteroskedasticity Test: ARCH				
F-statistic	12.74462	Prob. F(6,2236)	0.0000	
Obs*R-squared	74.17061	Prob. Chi-Square(6)	0.0000	
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Included observations: 2243 after adjustments				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	0.672540	0.072188	9.316549	0.0000
$WGT\_RESID^{2(-1)}$	-0.039920	0.021055	–1.896002	0.0581
$WGT\_RESID^{2(-2)}$	0.053558	0.021044	2.545049	0.0110
$WGT\_RESID^{2(-3)}$	0.069196	0.020944	3.303797	0.0010
$WGT\_RESID^{2(-4)}$	0.111207	0.020946	5.309265	0.0000
$WGT\_RESID^{2(-5)}$	0.051654	0.021046	2.454367	0.0142
$WGT\_RESID^{2(-6)}$	0.079567	0.021057	3.778705	0.0002
R-squared	0.033068	Mean dependent var		0.998297
Adjusted R-squared	0.030473	S.D. dependent var		2.681379
S.E. of regression	2.640209	Akaike info criterion		4.782709
Sum squared resid	15586.49	Schwarz criterion		4.800546

From Table 5, it can be seen that both the *F* statistic and the LM statistic are very significant thus suggesting the presence of ARCH in the daily sensex returns.

Table 7: GARCH (1,1) Results

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 4/02/2003 4/03/2012
Included observations: 2249 after adjustments
Convergence achieved after 20 iterations

Contd...

GARCH = C(3) + C(4)*RESID(–1)^2 + C(5)*GARCH(–1)				
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	0.001447	0.000269	5.386815	0.0000
RETURNS(–1)	0.074394	0.022697	3.277679	0.0010
Variance Equation				
C	5.92E-06	9.50E-07	6.229669	0.0000
RESID(–1)^2	0.133632	0.011192	11.93976	0.0000
GARCH(–1)	0.851177	0.011555	73.66468	0.0000
R-squared	0.002549	Mean dependent var		0.000896
Adjusted R-squared	0.002105	S.D. dependent var		0.017153
S.E. of regression	0.017135	Akaike info criterion		–5.614953
Sum squared resid	0.659728	Schwarz criterion		–5.602240
Log likelihood	6319.014	Hannan-Quinn criter.		–5.610312
Durbin-Watson stat	2.013415			

Table 7shows GARCH (1,1) model. The regression coefficients of the model are statistically significant @ 1 %. The sum of the coefficients of the variance equation(close to 0.98) is very close to unity and it suggests that conditional variance is present in the returns. A large sum of coefficients implies that a large positive or a large negative returns leads to high future forecast variance for a long period.

Table 8: Correlogram Analysis

Lags	*AC*	*PAC*	*Q –Stat.*	*Prob.*
1	0.016	0.016	0.5799	0.446
2	-0.020	-0.020	1.4769	0.478
3	0.024	0.025	2.7639	0.429
4	0.028	0.027	4.4970	0.343
5	-0.029	-0.029	6.4198	0.267
6	-0.033	-0.031	8.8224	0.184
7	0.023	0.022	10.047	0.186
8	0.010	0.009	10.286	0.246
9	0.017	0.021	10.938	0.280
10	0.027	0.026	12.546	0.250
11	-0.020	-0.024	13.461	0.264
12	0.003	0.004	13.486	0.335
13	0.016	0.015	14.076	0.368
14	0.031	0.031	16.210	0.301
15	-0.007	-0.004	16.332	0.360
16	0.012	0.012	16.654	0.408
17	0.033	0.028	19.154	0.320
18	-0.009	-0.009	19.323	0.372
19	-0.004	-0.001	19.366	0.434
20	-0.030	-0.031	21.383	0.375

Contd...

Lags	*AC*	*PAC*	*Q –Stat.*	*Prob.*
21	0.019	0.018	22.187	0.389
22	0.004	0.004	22.223	0.447
23	-0.018	-0.016	22.940	0.464
24	0.006	0.005	23.027	0.518
25	0.015	0.012	23.539	0.546
26	-0.001	-0.004	23.542	0.602
27	-0.028	-0.026	25.382	0.553
28	-0.004	-0.004	25.411	0.605
29	-0.034	-0.036	28.005	0.518
30	-0.029	-0.026	29.887	0.471
31	0.001	-0.001	29.887	0.523
32	-0.011	-0.011	30.167	0.560
33	-0.006	-0.004	30.241	0.605
34	0.009	0.008	30.409	0.644
35	0.002	-0.003	30.415	0.689
36	-0.020	-0.017	31.331	0.690

To test whether any ARCH effect is still present or not, Q-Statistic on the squared residuals has been calculated and the results are shown in Table 8. Since none of the Q-Statistic at any lag is significant, there is no ARCH effect left.

Table 9: TARCH (1,1) Results

Dependent Variable: RETURNS				
Method: ML - ARCH (Marquardt) - Normal distribution				
Sample (adjusted): 4/02/2003 4/03/2012				
Included observations: 2249 after adjustments				
Convergence achieved after 25 iterations				
GARCH = C(3) + C(4)*RESID(–1)^2 + C(5)*RESID(–1)^2*(RESID(–1)<0) + C(6)*GARCH(–1)				
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	0.001035	0.000272	3.804098	0.0001
RETURNS(-1)	0.087853	0.023562	3.728529	0.0002
Variance Equation				
C	7.57E-06	9.96E-07	7.598284	0.0000
RESID(-1)^2	0.056756	0.010595	5.357114	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.151561	0.020309	7.462933	0.0000
GARCH(-1)	0.843233	0.012454	67.70725	0.0000
R-squared	0.003198	Mean dependent var		0.000896
Adjusted R-squared	0.002754	S.D. dependent var		0.017153
S.E. of regression	0.017129	Akaike info criterion		–5.630638
Sum squared resid	0.659299	Schwarz criterion		–5.615382
Log likelihood	6337.652	Hannan-Quinn criter.		–5.625069
Durbin-Watson stat	2.041296			

Table 9 shows the estimated results of TARCH (1,1) model. The coefficients of the model are positive and since it is positive, there is leverage effect in the market. It can also be said that there exists news asymmetry and since the RESI value is positive and statistically significant, bad news has more effect on volatility of returns than good news. The findings are consistent with Chiang et al. (2001) and Som Sankar Sen et al. (2012) who have also used TARCH model to examine the volatility of seven Asian Stock Markets and BSE Sensex. They identified the presence of conditional volatility and asymmetry effect of stock returns.

Conclusion

The paper concludes that the return series of the time series data of BSE Sensex is stationary and not normally distributed. Also, the return series are serially correlated and thus there is autocorrelation. There is also evidence to suggest the presence of volatility clustering. An attempt has also been made to fit GARCH (1,1) model to study conditional variances. The regression coefficients are highly significant and Q-Statistic indicates that the equation is free from serial correlation. Therefore, GARCH (1,1) is a good fit to explore conditional variances. The coefficient value is close to unity and it can be concluded that a positive/negative return leads future forecasts of the variance to high / low for a long period of time. To capture the leverage effect, the study applied TARCH (1,1) model and the results show the presence of leverage effect in the market and there is news asymmetry in the market. The combined values of RESI and GARCH (-1) indicate that the bad news has more effect on the volatility than the good news.Also, the usage of Chow Test confirms that there are no breaks in data structures during the period of study. To conclude, the study has made an attempt to study the volatility in the returns of BSE Sensex and the model developed is a good fit in forecasting volatility. Future studies can focus on modelling volatility for different indices spread across the globe and establish the nature of volatility in these markets. Volatility transmission between markets is another area where research can be undertaken in the future.

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