AN EMPERICAL STUDY OF VOLATILITY OF SECTORAL INDICES (INDIA)

Author

Mrs. AP SHALINI
Hod (asst. Prof)
Villa marie pg college for women somajiguda

ABSTRACT

Volatility is plays a vital role in stock market's bull and bear phases. Although existence of volatility is the symbol of inefficient market, high volatility will also complements high return. Hence volatility modeling is vital for investment decisions and construction of portfolio. Several linear and non – linear models have been developed by many researchers to model the volatility of the stock market. The objective of this study is to model the volatility of the BSE Sectoral indices. The daily sectoral indices are taken from www.bseindia.com for the period of January, 2001 to June, 2014. The return of the BSE sectoral indices exhibits the characteristics of normality, stationarity and heteroskedasticity. Also the ACF and PACF indicate that ARMA (1,1) is the suitable one for modeling the average return. The residuals of the ARMA (1,1) of the sectoral index returns except for IT and TECH are heteroskedastic. Hence, a non-linear model is to found to model the volatility of the return series. An attempt is made to model the volatility of the return series and found that GARCH (1,1) model is the best one.

KEYWORDS: Sectors, Volatility, Non-linear models, ARMA, GARCH & Stationary.

INTRODUCTION

The study of volatility is remarkably important in many areas of quantitative finance. For example, study on variability in inflation rate, foreign exchange rate, stock market indices etc., Among the above the investors in the stock market are quite interested in the volatility of the stock prices. Investing in highly volatile stocks are of greater uncertainty. It may cause huge loss or gain. Several linear and non – linear models have been developed by many researchers to model the volatility of the stock market. The GARCH (1, 1) is often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (Bollerslev, Ray and Kenneth, 1992). In order to capture the leverage effect of the stock returns, i.e., conditional variance respond asymmetrically to the positive and negative shock of the returns(Mital and Goyal, 2012), models such as the Exponential GARCH (EGARCH) of Nelson (1991), the so-called GJR model of Glosten, Jagannathan, and Runkle (1993) were used. There are several works studying the stock market behaviour like stationarity, volatility etc. Most of the studies analyze the overall market index. Hence in this paper, an attempt is made to study the volatility characteristics of the sectoral indices of BSE using the GARCH.

1. LITERATURE REVIEW

Many researchers have developed several models to estimate and forecast the volatility of the stock market index. Few of those research works and publications are taken to understand the application of those models under different alternatives and the same is discussed below.

Abdullah Yalama and Guven Sevil(2008): Employed seven different GARCH class models to forecast in-sample of daily stock market volatility in 10 different countries emphasizing that the class of asymmetric volatility models perform better in forecasting of stock market volatility than the historical model.

Amita Batra(2004): In his working paper examined the time varying pattern of stock return volatility in India over the period 1979-2003 using monthly stock returns and asymmetric GARCH methodology.

Philip Hans Franses and Dick Van Djick (1996): Studied the performance of GARCH model and two of its non-linear models, QGARCH and GJR-GARCH to forecast weekly stock market volatility. They concluded that the QGARCH model is the best when the estimation sample does not have any extreme values.

Madhusudan Karmakar (2005): analyzed the 50 individual shares and inferred that various GARCH models provide good forecasts of volatility and are useful for portfolio allocation, performance measurement, option valuation, etc.

Dr Anil K. Mitta and Niti Goyal (2012): Analyzed the CNX nifty returns and summarized that that the return series exhibit heteroskedasticity, volatility clustering & has fat tails. GARCH (1, 1) is the most appropriate model to capture the symmetric effects and among the asymmetric model and PARCH (1, 1) to be the best as per Akaike Information Criterion & Log Likelihood criterion.

Abdul Rashid and Shabbir Ahmad (2008): Found that GARCH – class models dominate linear models of stock price volatility using RMSE Criterion. Different GARCH models were estimated by Thirupathiraju and Rajesh Acharya (2010) for various indices of NSE and BSE of Indian Stock market and inferred that GARCH(1,1) MA(1) in the mean equation was found to fit netter than the other models.

2. METHODOLOGY

The objective of this study is to model and forecast the volatility of the return series of BSE Sectoral indices. The daily sectoral indices are taken from www.bseindia.com for the period of January , 2001 to June, 2012. In this study, we follow a more robust approach as discussed below.

Return

IRJA-Indian Research Journal, Volume: 1, Series: 4. Issue: September, 2014 ISSN: 2347-7695
Online Available at www.indianresearchjournal.com

The monthly return of the BSE sectoral indices for the period starting from January 2001 to June 2012 is calculated as natural logarithm of the ratio between the current period index (Yt) and previous period share index Y(t-1). The formula is:

$$r_t = ln(Y_t|Y_{t-1}) ------------------ (1)$$

where r_t is the return in the period t, Yt is the monthly average for the period t, Y_{t-1} is the monthly average for the period t-1 and ln natural logarithm.

Normality

After finding the return, the first step is to check for the normality of the return using the summary statistics like Arithmetic mean, Median, Skewness, Kurtosis and Jarque-Bera test. If the Mean and Median are approximately equal, Skewness is zero, Kurtosis is around three and if the Jarque-Bera values is significant, then it is interpreted that the series follow normal distribution.

Stationarity

In order to test the stationarity of the data, Augmented Dickey-Fuller (ADF) test is used where the null hypothesis is that the series have unit root. Following equation checks the stationarity of time series data used in the study:

$$\Delta r_t = \mu + (\alpha - 1)r_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta r_{t-1} + \varepsilon_t \quad \text{--} (2)$$

Where ε_t is white noise error term in the model of unit root test, with a null hypothesis that return has unit root at time t. The test for a unit root is conducted on the coefficient of r_{t-1} in the
regression. If the coefficient is significantly different from zero (less than zero) then the null hypothesis is rejected

ACF and PACF for Stationarity and Heteroskedasticity

Stationarity of the return series can be determined using the Autocorrelation function (ACF) and Partial Auto correlation Function (PACF). Tintner defines autocorrelation as "lag correlation of a given series with itself, lagged by a number of time units". The autocorrelation at lag t by r_t is given by

$$r_t = \frac{\sum_{i=k+1}^{n}(Y_i - \bar{Y})(Y_{i-k} - \bar{Y})}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} ------------------ (3)$$

Together, the autocorrelations at lags 1, 2,….make up the autocorrelation function(ACF). When the autocorrelations are plotted against the lags, gives the correlogram. If the ACF and PACF
coefficient lie with in the critical values, $\pm 1.96\left(\frac{1}{N}\right)$, then the return is white noise.

MODELING VOLATALITY

Box Jenkins methodology is used to model the conditional mean equation. The correlogram of the series reflects a dynamic pattern which suggest for an ARMA model. The residuals of the equation are tested using LJUNG BOX Q-statistic for autocorrelation. The residuals are further tested for ARCH effects using ARCH LM Test.
Traditionally volatility modeling techniques were based on the assumption of homoskedasticity and were not able to capture the changing variance i.e. heteroskedasticity found in the returns. So more sophisticated models needed to be developed to capture such effects and leave the errors white noise. Thus non linear models such as ARCH/GARCH were developed to capture the features of the financial time series. The following GARCH techniques to capture the volatility have been used:

GARCH (1,1)

The GARCH specification, firstly proposed by Bollerslev (1986), formulates the serial dependence of volatility and incorporates the past observations into the future volatility (Bollerslev et al. (1994)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \text{--} (4)$$

News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate of β_1 shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

3. DATA ANALYSIS

Return - Normality

The table 1 below gives the summary statistics relating to the BSE sectoral indices.

Table 1: Table showing the summary statistics

Statistics	AUTO	BANKEX	CD	CG	FMCG	HC	IT
Mean	0.000893	0.000944	0.000671	0.000905	0.000552	0.000561	0.00027
Median	0.001392	0.001382	0.001361	0.001294	0.000535	0.000908	0.000453
Maximum	0.106266	0.175483	0.124785	0.198034	0.073378	0.077494	0.145016
Minimum	-0.11013	-0.1448	-0.1167	-0.15758	-0.11147	-0.08675	-0.22298
Std. Dev.	0.016443	0.020837	0.0201	0.019591	0.014011	0.012595	0.023623
Skewness	-0.3702	-0.09085	-0.33154	-0.055	-0.19684	-0.55245	-0.5014
Kurtosis	6.429047	8.582838	7.381602	10.38812	6.985996	7.95268	11.21313
Jarque-Bera	1472.171	3411.319	2350.026	6533.369	1919.162	3081.397	8192.522
Probability	0	0	0	0	0	0	0
Sum	2.563626	2.47727	1.927075	2.598991	1.585514	1.611159	0.775083
SumSq. Dev.	0.775966	1.138824	1.159924	1.101876	0.563412	0.455424	1.602083
Observations	2871	2624	2872	2872	2871	2872	2872

Table 1(Cont): Table showing the summary statistics

	METAL	OILGAS	POWER	PSU	REALTY	TECK
Mean	0.00074	0.000745	0.000368	0.000712	0.000146	0.00023
Median	0.001574	0.000778	0.001155	0.001685	0.001358	0.000685
Maximum	0.149282	0.174845	0.168265	0.151992	0.210645	0.131179
Minimum	-0.14272	-0.16211	-0.12134	-0.15564	-0.27957	-0.19811
Std. Dev.	0.023673	0.019675	0.019391	0.017855	0.032258	0.020981
Skewness	-0.37677	-0.36733	-0.05271	-0.43069	-0.4535	-0.55326
Kurtosis	6.85559	11.17835	9.985027	11.4834	9.157999	10.45157
Jarque-Bera	1846.863	8065.723	3792.3	8700.966	2605.506	6791.118
Probability	0	0	0	0	0	0
Sum	2.12588	2.137868	0.686908	2.045883	0.235515	0.65988
Sum Sq. Dev.	1.608931	1.110992	0.700855	0.915312	1.678419	1.263858
Obs	2872	2871	1865	2872	1614	2872

These descriptive statistics include mean, variance, standard deviation, skewness, kurtosis and Jarque-Bera statistics for normality test. From the statistics it may be inferred that the BSE sectoral returns in India are unlikely to have been drawn from a normal distribution. The returns are skewed negatively for the sample. The kurtosis statistic indicates that the returns are consistently leptokurtic. Furthermore, the Jarque-Bera statistic that tests the hypothesis of normal distribution is rejected at a very high level.

Stationarity

The table 2 gives the Augmented Dickey Fuller test for stationarity. The ADF test concludes that all the sectoral indices return are stationary at 1% level of significance.

ACF and PACF in table 3 also aids to test the stationarity and the volatility of the data. The ACF, PACF, Q-stat and Prob values of correlogram implies that the sectoral indices are

stationary. Also ACF and PACF coefficient lie within the critical values, $\pm 1.96\left(\frac{1}{N}\right)$, hence the sectoral returns are white noise.

Table 2: Augmented Dickey Fuller test for stationarity

S.NO	Sector	t-statistics	Prob	Result on Ho	Inference
1	Auto	46.45468	0.0001	Reject	Stationary
2	Bankex	-45.0545	0.0001	Reject	Stationary
3	CD	-48.4203	0.0001	Reject	Stationary
4	CG	-47.4452	0.0001	Reject	Stationary
5	FMCG	-52.0598	0.0001	Reject	Stationary
6	HC	-47.3736	0.0001	Reject	Stationary
7	IT	-39.6801	0.0000	Reject	Stationary
8	METAL	-47.5675	0.0001	Reject	Stationary
9	OIL & GAS	-48.557	0.0001	Reject	Stationary
10	POWER	-38.8667	0.0000	Reject	Stationary
11	PSU	-36.8259	0.0000	Reject	Stationary
12	REALTY	-34.2049	0.0000	Reject	Stationary
13	TECH	-39.7766	0.0000	Reject	Stationary

Table3: The ACF and PACF of return series

Sector	Lag	Return Series			
		AC	PAC	Q-Stat	Prob
AUTO	1	0.141	0.141	56.937	0.000
	2	-0.002	-0.022	56.952	0.000
	3	-0.003	0.001	56.975	0.000
BANKEX	1	0.126	0.126	42.025	0.000
	2	-0.026	-0.042	43.742	0.000
	3	-0.003	0.005	43.773	0.000
CD	1	0.100	0.100	28.96	0.000
	2	0.004	-0.006	29.002	0.000
	3	0.068	0.069	42.189	0.000
CG	1	0.120	0.120	41.404	0.000
	2	-0.028	-0.043	43.646	0.000
	3	0.028	0.037	45.858	0.000
FMCG	1	0.028	0.028	5.2361	0.035
	2	-0.036	-0.036	5.8936	0.053
	3	-0.03	-0.028	8.4077	0.038
HC	1	0.122	0.122	42.63	0.000
	2	0.012	-0.003	43.018	0.000
	3	0.025	0.024	44.804	0.000
IT	1	0.054	0.054	8.3909	0.004
	2	-0.071	-0.075	23.089	0.000
	3	-0.043	-0.036	28.519	0.000
METAL	1	0.118	0.118	39.856	0.000
	2	-0.005	-0.02	39.941	0.000

	3	0.023	0.026	41.434	0.000
OIL & GAS	1	0.098	0.098	27.346	0
	2	-0.033	-0.043	30.416	0
	3	-0.025	-0.017	32.147	0
POWER	1	0.103	0.103	19.878	0
	2	-0.002	-0.013	19.889	0
	3	0.014	0.016	20.252	0
PSU	1	0.151	0.151	65.54	0
	2	-0.03	-0.054	68.124	0
	3	0.016	0.03	68.893	0
REALTY	1	0.158	0.158	40.548	0
	2	0.083	0.059	51.563	0
	3	0.052	0.031	55.943	0
TECK	1	0.066	0.066	12.39	0
	2	-0.079	-0.083	30.12	0
	3	-0.027	-0.016	32.234	0

Modeling Mean:

The correlogram of the series reflects a dynamic pattern suggestive of an ARMA model to be used. AC & PAC coefficients are significant at the order of lag 1 & lag 2. ARMA (1, 1) model seems to be the best fit according to the Akaike Information Criterion to capture the dynamics of the series(table 4a).

The residuals of the equation are tested using LJUNG BOX Q Statistic for ACF and PACF significance and further tested for ARCH effects using ARCH LM Test. The values of AC and PAC coefficients, Q - statistics, F and corresponding probability values are given in table 4. Except for IT and Teck, the squared residuals have significant ACF and PACF. The F statistic reported by ARCH LM Test is significant and thus rejects the null hypothesis of no heteroskedasticity, except for IT necessitating the use of non linear models for capturing the volatility.

Modeling Volatality:

GARCH(1,1) Model:

Since the above analysis implies that the sectoral indices are highly volatile, an attempt is made to model the volatility of the sectoral indices. The following table 5 gives the coefficient of mean and variance equation of the GARCH(1,1)model. Since, Adjusted R Square for all the sectors are less than the R square, hence the parameters of the current GARCH(1,1) model itself explains the volatility better. All the co-efficient of both mean equation and variance equation are significant at 5% level. The model fit can also be inferred using the F and corresponding probability value. If probability value is less than 0.05 then the model is a good fit. Except for FMCG, IT and Teck, the model fits. Still for these sectors the residuals of the GARCH(1,1) model does not exhibit ARCH effect. The results of table 6 indicate that GARCH (1, 1) model is the best in modeling the conditional variance of the BSE Sectors as per Akaike Criterion, Schwarz criterion and Hannan –Quinn criterion & Log Likelihood Method. Akaike Criterion, Schwarz criterion and Hannan –Quinn criterion are least for this model and Log Likelihood is highest than the ARMA model. Durbin-Watson test value of all the sectoral indices lies nearer to 2, indicating the absence of autocorrelation.

Table 4: ARMA(1, 1) model residual diagnostics

Sector	Lag	RESIDUAL SERIES				Sq.Residual series					F	Prob	Obs R-squa
		AC	PAC	Q-Stat	Prob	Lag	AC	PAC	Q-Stat	Prob			
AUTO	37	0	0.002	4.01E+01	0.254	1	0.278	0.278	221.78		239.8535	0	221.4
	38	0.003	0.003	40.149	0.291	2	0.249	0.187	400.4				
	39	0.073	0.076	55.671	0.025	3	0.126	0.02	445.75	0			
BANKEX	4	-0.015	-0.015	8.34E-01	0.659	1	0.247	0.247	160.74		170.865	0	170.8
	5	-0.046	-0.046	6.3364	0.096	2	0.173	0.119	239.36				
	6	-0.063	-0.063	16.665	0.002	3	0.084	0.018	258.01	0			
CD	1	-0.001	-0.001	6.00E-03		1	0.229	0.229	150.42		158.3995	0	150.2
	2	0.017	0.017	0.8786		2	0.263	0.222	348.47				
	3	0.044	0.044	6.4099	0.011	3	0.174	0.085	435.41	0			
CG	6	-0.042	-4.20E-02	9.2086	0.056	1	0.229	0.229	150.43		158.4525	0	150.2
	7	0.016	0.015	9.9202	0.078	2	0.163	0.117	226.71				
	8	0.052	0.051	17.713	0.007	3	0.168	0.116	307.66	0			
FMCG	1	-0.002	-0.002	9.40E-03		1	0.345	0.345	342.77		388.4369	0	342.3
	2	-0.016	-0.016	0.7581		2	0.153	0.038	410.12				
	3	-0.033	-0.033	3.93	0.047	3	0.149	0.097	473.98	0			
HC	12	-0.008	-0.01	8.03E+00	0.626	1	0.4	0.4	460.81		547.7608	0	460.2
	13	0.053	0.052	16.043	0.14	2	0.23	0.083	612.7				
	14	0.046	0.046	22.16	0.036	3	0.182	0.077	707.69	0			
IT	51	-0.001	0.002	5.61E+01	0.289	1	0.024	0.024	1.6376	0.201	1.63712	0.2008	1.637
	52	-0.017	-0.022	57.008	0.294	2	-0.023	-0.024	3.196	0.202			
	53	-0.005	-0.009	57.097	0.325	3	0.007	0.008	3.3209	0.345			

Table 4(Cont): ARMA(1, 1) model residual diagnostics

Sector	Lag	RESIDUAL SERIES				Sq.Residual series						F	Prob		Obs R-squa
		AC	PAC	Q-Stat	Prob	Lag	AC	PAC	Q-Stat	Prob					
METAL	7	0.026	0.026	2.65E+00	0.754	1	0.301	0.301	259.84						
	8	0.057	0.057	12.084	0.06	2	0.218	0.141	396.86		285.		0		259.5
	9	0.03	0.031	14.757	0.039	3	0.241	0.16	563.79	0					
OIL & GAS	11	-0.02	-0.018	1.56E+01	0.076	1	0.243	0.243	169.03						
	12	-0.024	-0.025	17.304	0.068	2	0.191	0.14	273.93		179.235		0		168.8
	13	0.04	0.042	21.898	0.025	3	0.135	0.066	326.1	0					
POWER	6	-0.044	-0.044	3.88E+00	0.423	1	0.166	0.166	51.661						
	7	0.029	0.029	5.4641	0.362	2	0.22	0.197	141.68		52.98443		0		51.57
	8	0.077	0.078	16.654	0.011	3	0.175	0.12	198.56	0					
PSU	5	-0.023	-0.023	4.29E+00	0.232	1	0.283	0.283	229.87						
	6	-0.041	-0.041	9.1388	0.058	2	0.21	0.141	356.19		249.411		0		229.6
	7	0.044	0.043	14.594	0.012	3	0.15	0.066	420.96	0					
REALTY	62	0.018	2.20E-02	70.221	0.172	1	0.182	0.182	53.342						
	63	-0.044	-0.034	73.518	0.131	2	0.181	0.153	106.49		54.964		0		53.21
	64	0.102	0.098	90.844	0.01	3	0.116	0.064	128.39	0					
TECK	1	-0.003	-0.003	2.39E-02		1	0.266	0.266	204.03						
	2	-0.027	-0.027	2.1106		2	0.166	0.103	283.57						
	3	-0.041	-0.041	7.0024	0.008	3	0.12	0.057	324.96	0	219.1806		0		203.7
	8	0.019	0.018	12.048	0.061	2	0.007	0.007	0.1558						
	9	0.029	0.031	14.445	0.044	3	0.024	0.024	1.8045	0.179					

Table 4a: Model Diagnostics

Sector	ARMA(1,1)			
	Log Likelihood	AIC	SIC	HQC
AUTO	7746.654	-5.395577	-5.387268	-5.392582
BANKEX	6452.614	-4.918851	-4.909893	-4.915607
CD	7158.674	-4.985836	-4.977526	-4.98284
CG	7238.873	-5.041724	-5.033414	-5.038728
FMCG	8175.785	-5.696609	-5.688297	-5.693612
HC	8504	-5.923345	-5.915035	-5.920349
IT	6686.483	-4.656783	-4.648473	-4.653787
METAL	6692.322	-4.660852	-4.652542	-4.657856
OILGAS	7216.249	-5.027709	-5.019397	-5.024712
POWER	4712.685	-5.054949	-5.043076	-5.050574
PSU	7518.568	-5.236633	-5.228323	-5.233637
REALTY	3272.027	-4.054624	-4.041262	-4.049664
TECK	7030.899	-4.896794	-4.888484	-4.893798

4. SUMMARY

The return of BSE sectoral indices exhibit the characteristics such as normality, stationarity, autocorrelation and heteroscdaticity. Hence the volatility of the series cannot be predicted using ordinary least square method. Hence Boxjenkinson methodology is used to model the mean of the return series and ARMA(1,1) model is found to be the suitable one. Since the residual series of the ARMA(1,1) had ARCH effect, i.e, heterskedastics, a nonlinear model is to be fitted. Through analysis, it is concluded that GARCH(1,1) model as the best model to predict the volatility of the return series.

5. FUTURE RESEARCH:

The study can be extended to other stock market indices especially for NSE Sectoral indices. Also several other GARCH variants can be used to model the volatility and forecast the same.

References:

1. Abdul Rashid, Shabbit Ahmad . (2008) "Predicting Stock Return Volatility: An Evaluation of Linear and nonlinear methods', International Research Journal of Finance and Economics, 20, pg. 141-150
2. Abdullah Yalama, Guven Sevil. (2008) "Forecasting World Stock Markets Volatility", International Research Journal of Finance and Economics,15, pp.159 – 174.
3. Akgiray, V., (1989) "Conditional heteroscedasticity in time series of stock returns", Journal of Business, 62, pp. 55-80.
4. Alberg, D., Shalit, H., and Yosef, R. (2006) "Estimating stock market volatility using asymmetric GARCH models", Discussion Paper No. 06-10, Monaster Center for Economic Research, Ben-Gurion University of the Negev, Israel
5. Amita Batra. (2004) "Stock return volatility patterns in India", Working paper no. 124, Indian Council For Research On International Economic Relations, New Delhi.
6. Bollerslev, T., R. Y. Chou, and K. F. Kroner (1992)," ARCH Modeling in Finance: A Review of The Theory and Empirical Evidence", Journal of Econometrics, 52, pp. 5-60.
7. Dr Anil K. Mittal, Niti Goyal.,(2012) "Modeling The Volatility Of Indian Stock Market", IJRIM, Volume 2, Issue 1, pp.1-23.
8. Engle, R. F (1982), "Autoregressive Conditional Heteroscedasticity with estimates of the Variance of U.K. Inflation," Econometrica, 50, pp. 987-1008.
9. Franses, Philip Hans, Dick Van Dijk, (1996) "Forecasting Stock Market Volatility Using (nonlinear) Garch Models", *Journal of Forecasting*, Vol. 15, Iss. 3, pp. 229 – 235.
10. Glosten, L. R.; Jagannathan, R. y Runkle D.E. (1993). "On the Relation between the Expected Value and the Volatility of the Nominal Excess Returns of Stocks", Journal of Finance, 48, pp. 1779-1801.
11. Madhusudan Karmakar. (2005). "Modeling Conditional Volatility ofthe Indian Stock Markets", VIKALPA, 30(3), pp.21 – 37.
12. Nelson, B. D. (1991). "Conditional Heterocedasticity in Asset Returns: A New approach". Econometrica, 59(2), pp. 347-370.
13. M.Thiripalraju, Rajesh Acharya, H (2010) "Modeling volatility for the Indian stock market", The IUP jornal of Applied Economics, 9(1), pg. 79 - 105.