ANALYZING PERFORMANCE OF GARCH MODELS IN NSE

Voice of Research
Volume 3 Issue 2
September 2014
ISSN No. 2277-7733

Prashant Joshi
Professor and Head,
UKA Tarsadia University

Abstract

The study uses three different models: GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) to analyze volatility of Nifty of National Stock Exchange (NSE) of India from January 1, 2010 to July 4, 2014. The results reveal persistence of volatility andthe presence of leverage effect implying impact of good and bad news is not same. To evaluate the models, various model selection and forecasting performance criterion like AIC, SBC, RMSE, MAE, MAPE and TIC criterionare employed. Our results indicate that GARCH (1,1) has better forecasting ability in NSE.
JEL Classification: G14, C32

Key words : *Volatility clustering, GARCH, EGARCH, TGARCH, RMSE, MAE, MAPE, TIC*

Volatility of stock returns in developed stock markets received significant attention. After the seminal work of Engle(1982) on Autoregressive Conditional Heteroscedasticity (ARCH) model on UK inflation data and its Generalized form GARCH(Generalized ARCH) by Bollerslev (1986), much of the empirical work used these models and their extensions (See French, Schwert and Stambaugh 1987, Akgiray 1989, Schwert, 1990, Chorhay and Tourani,1994, Andersen and Bollerslev, 1998) to model characteristics of financial time series.

Variou features of stock returns have been extensively documented in the literature which are important in modeling stock market volatility. It has been found that stock market volatility is time varying and it also exhibits positive serial correlation (volatility clustering).This implies that changes in volatility are non-random. Moreover, the volatility of returns can be characterized as a long-memory process as it tends to persist (Bollerslev, Chou and Kroner, 1992). Schwert (1989) agreed with this argument. Fama (1965) also found the similar evidence. Baillie and Bollerslev (1991) observed that the volatility is predictable in the sense that it is typically higher at the beginning and at the close of trading period. Akgiray(1989) found that GARCH (1, 1) had better explanatory power to predict future volatility in US stock market.Poshakwale and Murinde (2001) modeled volatility in stock markets of Hungary and Poland using daily indexes. They found that GARCH(1,1) accounted for nonlinearity and volatility clustering. Poon and Granger (2003) provided comprehensive review on volatility forecasting. They examined the methodologies and empirical findings of 93 research papers and provided syneptic view of the volatility literature on forecasting. They found that ARCH and GARCH classes of time series models are very useful in measuring and forecasting volatility. In the Indian Context, Roy and Karmakar (1995) focused on the measurement of average level of volatility as the standard deviation in the Indian Stock Market and examined that volatility was highest in the year 1992. Goyal (1995) examined the nature and trend of the stock return volatility in the Indian Stock Market and assessed the impact of 'carry forward facility' on the level of volatility. Reddy (1997) analyzed the establishment of NSE and introduction of BSE online trading (BOLT) on the stock market volatility as sample standard deviation. Kaur (2002) analyzed the extent and pattern of stock market volatility, modeled the volatility during 1990-2000 and examined the effect of company size, FII, day of the week effect on volatility. Ajay Pandey (2002) modeled the volatility of S & P CNX Nifty using different class of estimators and ARCH /GARCH class of models.

Balaban, Bayar and Faff (2002) investigated the forecasting performance of both ARCH-type models and non-ARCH models applied to 14 different countries. They observed that non-ARCH models usually produce better forecast than ARCH type models. Finally, Exponential GARCH is the best among ARCH-type models. Pan and Zhang (2006) use Moving Average, Historical Mean, Random Walk, GARCH, GJR-GARCH, EGARCH and APARCH to forecast volatility of two Chinese Stock Market indices; Shanghai and Shenzhen. The study found that Among GARCH models, GJR-GARCH and EGARCH outperforms other ARCH models for Shenzhen stock market.

Magnus and Fosu (2007) employed Random Walk, GARCH(1,1), TGARCH(1,1) and EGARCH(1,1) to forecast Ghana Stock Exhange. GARCH(1,1) provides the best forecast according to three different criterias out of four. On the other hand, EGARCH and Random Walk produces the worst forecast.

Foregoing discussion suggests that the modeling of the stock markets volatility and its forecasting is of great importance to academics, policy makers, and financial markets participants. Predicting volatility might enable one to take risk-free decision making including portfolio selection and option pricing. High levels of volatility in a stock market can lead to a general erosion of investors' confidence and an outflow of capital from stock markets, volatility has become a matter of mutual concern for government, management, brokers and investors. It is therefore necessary for us to explore stock market volatility and also identify a model that gives better prediction.

The rest of the paper is organized as follows. Section II provides research design used in the study. Empirical results are discussed in Section III. Section IV summarizes.

Research Design

Period of study

We collected data on daily closing price of Nifty of National

Stock Exchange from January 1, 2010to June 27, 2014.It consists of 1122 observations. The period of the study is the most recent one. These stock markets have become increasingly integrated.The trades between countries have increased. They are playing an important role in the world economy. These might have influenced the behaviorand the pattern of volatility and therefore it will be instructive to analyze volatilityin this period.

Methodology

Daily returns are identified as the difference in the natural logarithm of the closing index value for the two consecutive trading days.

Volatility is defined as;

$$\sigma = \sqrt{1/n-1\sum_{t=1}^{n}(R_t - \bar{R})^2} \qquad \textbf{Equation 1}$$

where $\bar{R}$ = Average return(logarithmic difference) in the sample.

In comparing the performance of linear model with its non-linear counterparts, we first used ARIMA models. Nelson (1990b) explains that the specification of mean equation bears a little impact on ARCH models when estimated in continuous time. Several studies recommend that the results can be extended to discrete time. We follow a classical approach of assuming the first order autoregressive structure for conditional mean as follows:

$$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t \qquad \textbf{Equation 2}$$

where R_t is a stock return, $a_0 + a_1 R_{t-1}$ is a conditional mean and ε_t is the error term in period t. The error term is further defined as:

$$\varepsilon_t = \upsilon_t \sigma_t \qquad \textbf{Equation 3}$$

where υ_t is white noise process that is independent of past realizations of . ε_{t-i} It has zero mean and standard deviation of one. In the context of Box and Jenkins (1976), the series should be stationary before ARIMA models are used. Therefore, Augmented Dickey Fuller test (ADF) is used to test for stationarity of the return series.It is a test for detecting the presence of stationarity in the series. The early and pioneering work on testing for a unit root in time series was done by Dickey and Fuller (1979 and 1981).If the variables in the regression model are not stationary, then it can be shown that the standard assumptions for asymptotic analysis will not be valid. ADF tests for a unit root in the univariate representation of time series. For a return series Rt, the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i=1}^{p}\beta_i \Delta r_{t-i} + \varepsilon_t$$

$$\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t) \qquad \textbf{Equation 4}$$

The null hypothesis is H0: $\delta = 0$ and H1: $\delta < 1$ The acceptance of null hypothesis implies nonstationarity.We can transform the nonstationary time series to stationary time series either by differencing or by detrending. The transformation depends upon whether the series is difference stationary or trend stationary.

One needs to specify the form of the second moment, variance, σ_t^2 for estimation.ARCHand GARCHmodelsassume conditional heteroscedasticity with homoscedastic unconditional error variance. That is, the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random departure from a constant unconditional variance. The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. It, therefore, enables us to make the connection between information and volatility explicit since any change in the rate of information arrival to the market will change the volatility in the market. In empirical applications, it is often difficult to estimate models with large number of parameters, say ARCH (q). To circumvent this problem, Bollerslev (1986) proposed GARCH (p, q) models. The conditional variance of the GARCH (p,q) process is specified as

$$h_t = \alpha_0 + \sum_{j=1}^{q}\alpha_j \varepsilon_{t-j}{}^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \qquad \textbf{Equation 5}$$

with $\alpha_0 > 0, \alpha_1, \alpha_2, ...\alpha_q \geq 0$ and $\beta_1, \beta_2, \beta_3, \ldots\ldots\ldots, \beta_p \geq 0$ to ensure that conditional variance is positive. In GARCH process, unexpected returns of the same magnitude (irrespective of their sign) produce same amount of volatility. The large GARCH lag coefficients ?i indicate that shocks to conditional variance takes a long time to die out, so volatility is 'persistent.' Large GARCH error coefficient ?j meansthat volatility reacts quite intensely to market movements and so if ?j isrelatively highand?i is relativelylow, then volatilities tend to be 'spiky'. If $(\alpha + \beta)$ is close to unity, then a shock at time t will persist for many future periods. A high value of it implies a 'long memory.'

EGARCH Model

GARCH models successfully capture thick tailed returns, and volatility clustering, but they are not well suited to capture the "leverage effect" since the conditional variance is a function only of the magnitudes of the lagged residuals and not their signs.

In the exponential GARCH (EGARCH) model of Nelson (1991) $\sigma_t{}^2$ depends upon the size and the sign of lagged residuals. The specification for the conditional variance is:

$$\log(\sigma_t{}^2) = \alpha_0 + \sum_{j=1}^{q}\beta_j \log(\sigma_{t-j}{}^2) + \sum_{i=}^{p}\alpha_i \frac{|\varepsilon_{t-i}|}{|\sigma_{t-i}|} + \sum_{h=1}^{r}\gamma_h \frac{\varepsilon_{t-h}}{\sigma_{t-h}}$$

Equation 6

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative thus eliminating the need for parameter restrictions to impose non-negativity as in the case of ARCH and GARCH models. The presence of leverage effects can be tested by the hypothesis that $\gamma_h < 0$. The impact is asymmetric if $\gamma_h \neq 0$.

TGARCH Model

In ARCH / GARCH models both positive and negative shocks of same magnitude will have exactly same effect in the volatility of the series. T-GARCH model helps in overcoming this restriction. TARCH or Threshold GARCH model was introduced independently by Zakoin (1994) and Glosten, Jaganathan and Runkle (1993). The generalized specification for the conditional variance is given by:

$$\sigma_t^{\,2} = \alpha + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\,2} + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^{\,2} + \sum_{h=1}^{r} \gamma_h \varepsilon_{t-h}^{\,2} d_{t-h}$$

Equation 7

Where $d_t = 1$ if $\varepsilon_t < 0$ and zero otherwise.

In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$, have differential effect on the conditional variance; good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If , $\gamma_i > 0$ bad news increases volatility, and we say that there is a leverage effect for the i-th order. If $\gamma_i \neq 0$, the news impact is asymmetric. The main target of this model is to capture asymmetries in terms of positive and negative shocks.

Forecasting Evaluation

Root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil inequality coefficient (TIC) are employed to measure the accuracy of the forecasting models.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=184}^{365} (\sigma_{a,t} - \sigma_{f,t})^2}{182}}$$

$$\text{MAE} = \frac{\sum_{t=184}^{365} |\sigma_{a,t} - \sigma_{f,t}|}{182}$$

$$\text{MAPE} = 100 \; \frac{\sum_{184}^{365} \left| \frac{\sigma_{a,t} - \sigma_{f,t}}{\sigma_{a,t}} \right|}{182}$$

$$\text{TIC} = \frac{\sqrt{\frac{\sum_{184}^{365} \left(\sigma_{a,t} - \sigma_{f,t}\right)^2}{181}}}{\sqrt{\frac{\sum_{184}^{365} \sigma_{a,t}^{\,2}}{182}} + \sqrt{\frac{\sum_{184}^{365} \sigma_{f,t}^{2}}{182}}}$$

Where $\sigma_{a,t}$ is the actual volatility $\sigma_{f,t}$ and is the forecasted volatility.

The model with better forecasting power has lower values of all the above measures compare to other models.

III. Empirical results

The descriptive statistics for the return series include mean, standard deviation, skewness, kurtosis,Jarque-Bera and Ljung Box. ARCH-LM statistics are also exhibited in the Table 1.

Table 1

Descriptive Statistics of Daily Returns

Statistic	Nifty
Mean	0.00071
Standard deviation	0.01342
Skewness	1.14196
Kurtosis	18.95906
Jarque-Bera Statistics	14706.5(0.000)
$Q^2(12)$	62.96(0.000)
ARCH LM statistics (at Lag =1)	1.09(0.29)
ARCH LM statistics (at Lag =5)	11.59(0.041)

Notes:ARCH LM statistic is the Lagrange multiplier test statistic for the presence of ARCH effect. Under null hypothesis of no heteroscedasticity, it is distributed as $\lambda^2(k)$ .Q2(K) is the Ljung Box statistic identifying the presence of autocorrelation in the squared returns. Under the null hypothesis of no autocorrelation, it is distributed as $\lambda^2(k)$.

The mean returns for all the stock indices are very close to zero indicating that the series are mean reverting. The return distribution is negatively skewed, indicating that the distribution is non-symmetric. Large value of Kurtosis suggests that the underlying data are leptokurtic or thick tailed and sharply peaked about the mean when compared with the normal distribution. Since GARCH model can feature this property of leptokurtosis evidence in the data.

The Jarque-Bera statistics calculated and reported in the Table-1 to test the assumption of normality. The results show that the null hypothesis of normality in case of both the stock markets is rejected.

The Ljung-Box LB2 (12) statistical values of all the series respectively rejects significantly the zero correlation null hypothesis. It suggests that there is a clustering of variance. Thus, the distribution of square returns depends on current square returns as well as several periods' square returns, which will result in volatility clustering.

Stationarity condition of the Sensexdaily return series were tested by Augmented Dickey-Fuller Test (ADF). The results of this test are reported in the Table2.

Table 2
Unit Root Testing of Daily Returns of Sensex Augmented Dickey-Fuller Test

Level	Return
-0.77(0.83)*	-31.83(0.00)

ADF statistics in level series shows presence of unit root in the stock marketsas its probability value is greater than 0.05. It suggests that the price series is nonstationary. It is, therefore, necessary to transform the series to make it stationary by taking its first difference. ADF statistics reported in the Table 2 show that the null hypothesis of a unit root is rejected. The computed values for the index isstatistically significant. Thus, the result shows that the first difference series is stationary.

To test for heteroscedasticity, the ARCH-LM test is applied to the series. The results are reported in Table 1. The ARCH-LM test at lag length 1 and 5 indicate presence of ARCH effect in the residuals in both the stock markets. It implies clustering of volatility where large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes(Engle,1982 and Bollerslev, 1986). The Conditional volatility of returns may not only be dependent on the magnitude of error terms but also on its sign. We checked for asymmetry in both the stock markets using EGARCH and TARCH models. The results are reported in Table 3.

Table 3
Coefficients of Asymmetric Models

Coeffiecients	GARCH(1,1)	EGARCH(1,1)	TARCH(1,1)
α_0	0.0000(0.000)	-0.5952(0.000)	0.0000(0.000)
α_1	0.06722(0.000)	0.2070(0.000)	0.0396(0.000)
β_1	0.9029(0.000)	0.9726(0.000)	0.8792(0.000)
$\alpha_1+\beta_1$	0.9701		
γ		-0.0908(0.005)	
(RESID(-1)^2)* RESID(-1)<0)			0.1262(0.005)
AIC	-6.268443	-5.829751	-5.835052
SBC	-6.246027	-5.814026	-5.819326
ARCH-LM(5) Test	5.815(0.324)	3.207(0.668)	5.132(0.40)

The above findings indicate that there is no ARCH effect left after estimating the models because the results of F-statistics or ARCH-LM test after fitting the model are statistically insignificant as its probability value is higher than 0.05. It, therefore, suggests that the estimated models are better fit.

Conditional volatility of returns may not only be dependent on the magnitude of error terms but also on its sign. We checked for asymmetry in both the stock markets using EGARCH and TARCH models. The results are presented in the Table 3.

The analysis of this EGARCH model suggests that its coefficient (-0.0908) is significant, the leverage effect term ? is negative and statistically different from zero, indicating the existence of leverage effect in the stock market returns during the sample period.

Similarly, results of TARCH model estimation are listed in Table 3. Most importantly, the leverage term (γ), represented by (RESID(-1)^2)* RESID(-1)<0) is here greater than zero and highly significant. Its values is 0.1262. This reinforces the assumption that negative and positive shocks have different impact on the volatility of daily returns. Here good news has an impact of ?1 = 0.0396, while the bad news has an impact of $\alpha_1+\gamma$ whichis equal to 0.1658. Thus, it can be said that negative or bad news creates greater volatility than positive or good news in both the stock markets.

The model selection criterion AIC and SBC reported in table 3 select GARCH(1,1) models as their values are smallest for GARCH(1,1) models. Now, we evaluate the models on the basis of their forecasting accuracy. The results are reported in Table 4.

Table 4
Volatility Forecasting Evaluation

Model	RMSE	MAE	MAPE	TIC
GARCH(1,1)	0.000125	0.000094	1042	0.5111
EGARCH(1,1)	0.000129	0.000101	1123	0.5086
GJR-GARCH(1,1)	0.000132	0.000105	1196	0.5052

Table 4 gives the actual forecast error statistics for each model. In the case of RMSE, MAE and MAPE, GARCH provides the best volatility forecast. The Theil Inequality Coefficient (TIC) is a scale invariant measure that always lies between Zero and one, where Zero indicates a perfect fit. Looking at this coefficient we can say that GJR-GARCH(1,1) model is the best forecasting model. All the forecasting measures hints at GARCH(1,1) model for better forecasting of conditional volatility.

IV. Summary

The volatility in the Nifty exhibits the persistence of volatility, mean reverting behavior and volatility clustering. Various diagnostic tests indicate volatility clustering and the response to news arrival is asymmetrical, meaning that impact of good and bad news is not the same. By the application of asymmetrical GARCH models like EGARCH and TARCH, we conclude that there is a presence of leverage effect in both the stock markets in India. These models suggest that the volatility appears to be more when price decline than when price increases.

We evaluated the models on the basis of model selection criterion and their forecasting accuracy.We used AIC and SBC criteria to select best fitting model and RMSE. MAE, MAPE and TIC to check their forecasting accuracy. Our results indicate that GARCH (1,1) is the best forecasting model.

References

Akgiray, V., (1989). 'Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecast, *Journal of Business*, 62(1), 55-80.

Andersen, T. G. and Bollerslev, T., (1998). Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts, *International Economic Review*, 39(4), 885-905.

Ane T., (2006). Short and long term components of volatility in Hong Kong stock returns, *Applied Financial Economics*, 16, 439-460.

Baillie, R T and Bollerslev, T., (1991). Intra-day and Inter-market Volatility in Foreign Exchange Rates, *Review of Economic Studies,* 58(3), 567-585.

Balakrishnan, R., Danninger S., Elekdag S, and Tytell I. (2009). *The Transmission of Financial Stress from Advanced to Emerging Economies.* IMF Working Paper No. 09/133.

Bollersflev, Chou R.Y.and Kroner K.F., (1992). ARCH modeling in finance : A review of the theory and empirical evidence, *Journal of Econometrics*, 52, 5-59.

Bollerslev,T., (1986) Generalised Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics*, 51, 307-327.

Box, G. E. P. and Jenkins, G. M., (1976). *Time Series Analysis: Forecasting and Control*, revised edition, California: Holden-Day.

Brock, Dechert, Scheinkman and Le Baron (1996). A test for independence based on the correlation dimension, *Econometric Review*, 15, 197-235.

Corhay, A and Tourani, A.R., (1994).Statistical Properties of Daily Stock Returns: Evidence from European Stock Markets, *Journal of Business Finance and Accounting*, 21(2), 271-282.

Dickey D. and Fuller W., (1979). Distribution of the estimates for Autoregressive time series with a unit root, *Journal of American Statistical Association*, 74, 427-31.

Dickey, D. & Fuller W., (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root, *Econometrica*, 49, 1057 – 72

Engle, R., (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation, *Econometrica*, 50(4), 987-1008.

Fama, E., (1965). The Behaviour of Stock Market Prices, *Journal of Business*, 38(1), 34-105.

Frances, P. H. and D. V. Dijk (1996). Forecasting stock market volatility Using (Non-Linear) Garch Models, *Journal of Forecasting*, Vol. 15, 229-235.

French,K,Schewert, G. and Stambaugh, R., (1987). Expected Stock Returns and Volatility, *Journal of Financial Economics*, 19(1), 5-26.

Goyal, R(1995). Volatility in Stock Market Returns, Reserve Bank of India *Occasional Paper*, 16(3), 175-195.

Kaur, H (2002). *Stock Market Volatility in India*, New Delhi: Deep and Deep Publication.

M.K.Roy and M.Karmakar,(1995). Stock Market Volatility: Roots and Results, *Vikalpa*,37-48.

M.Karmakar, (2005). Modeling Conditional Volatility of the Indian Stock Markets, *Vikalpa*, 30. 21-37

M.Karmakar,(2005). Stock Market Volatility in the Long Run, 1961-2005, *Economic and Political Weekly*, 1796-2000.

Magnus, F. J. and O. A. E. Fosu (2006). *Modeling and Forecasting Volatility of Returns in the Ghana stock Exchange using GARCH Models,* MPRA Paper, No.593.

Mandelbrot, B., (1963).The Variation of Certain Speculative Prices, *Journal of Business*, 36, 394-419.

Nachane, D. M., (2007). *Econometrics-Theoretical Foundations and Empirical Perspectives*, Oxford University Press, India.

Nelson, D. B.,(1990a).Conditional Heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, 59, 347-70.

Nelson, D. B.,(1990b) ARCH models as diffusion approximations, *Journal of Econometrics*, 45, 7-38.

Pan, H. and Z. Zhang (2006). *Forecasting financial Volatility: Evidence from Chinese Stock market*, Durham business School Working Paper Series, 2006.02.

Pandey, A (2002). *Modeling and Forecasting Volatility in Indian Capital Markets*, Paper published as part of the NSE Research Initiative, available at www.nseindia.com

Poon, S H and Granger, C.,(2003). Forecasting Financial Market Volatility: A Review, *Journal of Economic Literature*, 41(2), 478-539.

Poon, S. H. and C. Granger, (2003). Forecasting Volatility in Financial Markets: A review, *Journals of Economic Literature*, XLI, 478-539.

Poshakwale and Murinde (2001).Modelling the volatility in East European emerging stock markets: evidence on Hungary and Poland, *Applied Financial Economics*, 11, 445-456.

Reddy, Y S (1997). Effects of Microstructure on Stock Market Liquidity and Volatility, *Prajan*, 26(2), 217-231.

Schwert, G W.,(1990). Stock Volatility and the Crash of 87, *Review of Financial Studies*, 3(1), 77-102.

Schwert, G.W.,(1989). Why does Stock Market Volatility Change Over time?, *Journal of Finance*, 54, 1115-1153.

Taylor, S. J. (1987). Forecasting the Volatility of Currency Exchange rates, *International Journal of Forecasting*, 3, 159-170.

Tse, S. H. and K. S. Tung (1992). Forecasting Volatility in the Singapore Stock Market, *Asia Pacific Journal of Management*, 9, 1-13.

Tse, Y.K. (1991). Stock Returns volatility in the Tokyo Stock Exchange, *Japan and The World Economy*, 3,258-298.