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A STUDY OF MODELING VOLATILITY IN STOCK MARKET OF INDIA

ABSTRACT

Volatility plays an important role in financial world. After LPG process in India, volatility ups in stock markets.This study analyzed the volatility features of stock prices of India, using monthly closing price of Nifty for ten years (January 2006 to December 2015). The study of features of volatility like volatility clustering, leverage effect made in this study. Diagnostic test like LJung box (Q) statistic, ARCH LM test & Jarque-Bera test used for goodness of fit of Model. Volatility clustering observed in stock returns but leverage effect not observed. Even volatility pattern was asymmetrical.

Key Words: *Volatility Clustering, GARCH, EGARCH, TGARCH model, Leverage effect*

1. INTRODUCTION:

Now-a-days volatility plays an important role in financial management. Everybody (Investors, Traders, Businessmen etc.) take interest to understand features of volatility. Traditionally volatility measure through variance(standard deviation) which assumed constant in modeling. This concept changed after Engle's seminal work (1982). He present a paper on conditional volatility. He argued that in some time series like stock return's volatility is not constant but conditional over time. It is a past disturbances' function. Technically this is known as (Autoregressive Conditional Heteroscedasticity) ARCH process. In 1986 Bolerslev modified this theory and present GARCH model. He believed that conditional variance of stock return is not only function of past disturbances but previous variance also. This theory accepted and large scale used. Through ARCH & GARCH model we know volatility clustering but there are some important features can't know. The asymptotic effect of volatility cannot know. In 1991 Nelson modified this model and present Exponential Generalised ARCH (EGARCH) model and in 1993 & 1994 GJR & Zakoian found Threshhold GARCH (TGARCH) model which captures this asymetric effect of volatility of stock prices.

These model's are vast used for analyzed or investigated stock return data in developed countries but in emerging countries like India, China, & all other Asian countries less work done. H. Kaur(2004), Karmakar (1995 & 2005) , Jagdish Joshi (2010) did some work in this area. In this paper investigated such features of volatility in Stock Market of India. In Stock Market of India, CNX Nifty, which is representative of Stock Market of India. In this paper tried to estimate GARCH(1,1), EGARCH(1,1) & TGARCH(1,1) model. To checked goodness of fit of above model diagnosis test like LJungbox (Q) statistic, ARCH LM test, Jarque-Bera test & ADF test used.

2. REVIEW OF LITERATURE:

Poterba and Summers (1984) evaluated volatility's effect in stock returns.To obtained volatility estimates monthly stock return data from 1926 to 1983 were used. It demonstrated that serial correlation of volatility was weak means shocks to volatility do not long term persist. These shocks can, therefore, have only little impact on stock market return.Since movement in volatility affect expected required rates of return for relatively short time periods. Empirical results suggest that changes in volatility should affect expected required returns for periods not substantially greater than two years. To know serial correlation ACF & PACF technique used.

Kaur (2004) investigated eminent features of volatility in stock market of India during 1993-2003. The features of volatility like volatility clustering, day-of-the-week effect, month –of- the- year effect, she observed in her research work. She observed that asymmetrical nature of GARCH models captures the different features of the volatility and hence it is superior than the conventional Ordinary Least Square(OLS) models and symmetrical GARCH models. She realized that the asymmetrical GARCH models like EGARCH (1,1) & TARCH (1,1) are good fit for sensex & Nifty returns.

Karmakar (2005) investigated features of stock return's volatility models. He used the GARCH models to investigate volatility of stock return changes over time and it will predictable. The GARCH (1,1) model has been fitted for returns of all companies. In four companies, the GARCH models of higher order found more successful. The GARCH (1, 1) model estimated and then evaluated in terms of forecast accuracy on two market indices: NSE Nifty and BSE Sensex. The result of study suggested conditional volatility, which exhibits clustering, high persistence and predictability.

Prashant Joshi (2010) studied of volatility features of the emerging stock markets;India and China. He used daily closing stock price of Nifty for ten years (from January 2005 to May 2009). He has used BDSL test to know non-linearity and ARCH-LM test for conditional Heteroscedasticity of volatility. The findings exhibits that the GARCH(1,1) model fit for captureing nonlinearity and volatility clustering.

Sathya Swaroop Debasish(2011) Attemped to investigate, because of start up of future trading in stock market of India. The study was carried out of Nifty, CNX IT, CNX Bank for the period January 1997 to May 2007. In this study near month contract investigated because they are heavily traded. In this study, volatility of inter-day between spot prices and futures prices' hypothesis over the entire period rejected for all three indices. The study applied four measure of volatility namely close to close, open to open, Garman-Klass volatility measure. To test above hypothesis, He has used F-test.

3. ECONOMETRIC MODELS OF PREDICTABLE VOLATILITY:

In the study of volatility, it is important to know prediction.There are some important models which serve the purpose of study, which are as follows

ARCH MODEL:

In 1982 Engle present seminal paper about ARCH (Autoregressive Conditional Heteroscedasticity) model for the time series data.Engle suggests that the conditional variance h_t can be modeled as a function of the lagged residual term Ɛ's. That is forcasted volatility is dependent on past news. Following are the ARCH (q) model:

$$h_t = w + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots \ldots \ldots + \alpha_q \varepsilon_{t-q}^2$$

GARCH MODEL:

Bollerslev (1986) generalized the ARCH (q) model to the GARCH (p, q) model.According to him, variance of residual at t time is dependent on previous residual term as well as variance also.The eminent features of GARCH model is that it captures the trend in financial data for volatility clustering. GARCH (p,q) model are as follows,

$$h_t = w + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots \ldots \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \cdots \ldots + \beta_p h_{t-p}$$

EGARCH MODEL:

Even simplicity of ARCH & GARCH model, some important features cannot captures. Among them one feature is asymmetric or leverage effect. For that in 1991 Nelson suggest one modification in GARCH model and developed Exponential GARCH model. This model captures this leverage effect. EGARCH(1,1) model are as follows:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left(\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right)$$

TGARCH MODEL:

Same purpose serve through this model.This model developed in 1993 by Glosten, Jagnnathan and Runkle and in 1994 by Zakoian with minor change. This model also noticed leverage effect.Statistically this effect happens when unexpected drop in price(**bad news**) increases predictable volatility more than an unexpected increases in price (**good news**) of similar magnitude.

$$h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\varepsilon_{t-1}^2 d_{t-1}$$

Where $d_{t-1} = 1, if\ \varepsilon_t^2 < 0$ and $d_{t-1} = 0, other\ wise$

4. DIAGNOSTIC TEST:

After fitting above model, one can use to test the fitting model is proper or not. There are different tests used for different objectives. In this study following tests used.

(1) **LJungbox (Q) statistics** : To detect volatility clustering means high volatility follow high volatility and low volatility follow low volatility this test is widely used. In 1978 LJungbox has developed this test. In this test one can know is there any serial correlation in residual terms. If there is serial correlation is found means volatility clustering is present. Q statistics defined in following way,

$$Q = \frac{n(n+2)\sum r_k^2}{n-k}$$

Where n = sample size & k = lag length

For large sample Q follow $\chi 2$ distribution. If calculated Q is greater than tabulated than Hypothesis of no serial correlation rejected otherwise accepted.

(2) **Lagrange Multiplier ARCH test** :

In 1982 Engle suggest this test to detect ARCH effect in residual. The variance of error may depend on several lagged squared terms as follows:

$Var\ (u_t) = \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots . + \alpha_p u_{t-p}^2$

A simple Lagrange Multiplier (LM) test for ARCH effects may be constructed based on the auxiliary regression as in above equation. Under the null hypothesis that there is no ARCH effects:

$$H_0 = \alpha_1 = \alpha_2 = \cdots = \alpha_P = 0$$

The test statistic is $LM =\ .T.\ R^2 \sim \chi 2_{(p)}$

where T is the sample size and R^2 is computed from the above regression equation using estimated residuals. That is in a large sample, TR^2 follows the Chi-square distribution. The test statistic is defined as TR^2 (the number of observations multiplied by the coefficient of multiple correlation) from the last regression, and it is distributed as a χ_q^2 (Gujarati, 2007).

(3) **Jarque- Bera (Normality) test** :

This test check the normality assumption hold good in residual or not. Carlos Jarque & Anil k Bera found this test. Test statistics of this test is

$$JB = \frac{n}{6}\left(s^2 + \frac{1}{4}\,(k-3)^2\right)$$

Where n is observation's number , S is sample Skewness & K is sample Kurtosis.

(4) Unit root test (ADF test):

Generally time series data is non- stationary at level. If time series data is not stationary than result obtained may be spurious. So first check given time series data is stationary or non stationary. This is unit root problem. So enormously used test is ADF test. AR(1) model is as follows

$$Y_t = c + \delta Y_{t-1} + \varepsilon_t$$

Where c & δ are parameters and assumed white noise. If $-1 < \delta < +1$ then y_t is a stationary series, and $\delta = 1$ then non-stationary. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series is involves whether the absolute value of ρ is strictly less than one.

The null hypothesis is $H_0 : \delta = 0$ vs $H_1 : \delta = 1$

If the p value is less than significant level 0.05 than null hypothesis will be rejected otherwise accepted.

5. RESEARCH METHDOLOGY:

In this study following path used in carried out research.

Objectives: Following objectives used in this study.

- To know volatility clustering during study period
- To know asymmetric or leverage effect of volatility

Hypothesis: Following are the hypothesis of the study

- H_{01} : There is no volatility clustering observed during study period
- H_{02} : There is no asymmetric or leverage effect of volatility

Sample Design:

Study Period: Study period was from January 2006 to December 2015. During this period world economic crises happened in 2008-09. Government changed in 2009 & 2014, so policy of their were different. So volatility nature is important to study during this years.

Sample Study : As a study sample, Nifty & Sensex are two representative of Indian stock market, so both take into consideration for study.Their monthly closing prices are used. To calculate **return** following formula used.

If **It** be the closing level of Sensex & Nifty on date t and **It-1** be the same for its previous business month, , then the one month return on the market portfolio is calculated as:

$$r_t = \ln (It/It\text{-}1)\text{x}100$$

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

Data of Nifty & Sensex taken from website of yahoo finance & money control .com & Nifty website.

Statistical Tools : First With the Microsoft Excel return obtained through above way, then with the help of econometric software **eviews** & **num xl** volatility & its features calculated.

6. EMPIRICAL FINDINGS & ANALYSIS:

We start with ploting graph which are in Figure1 & 2. Figure 1 is for Nifty Monthly closing values & Figure 2 Nifty monthly returns. Figure 1 exhibit that future prediction is not possible, which shows random walk. So on the observation one can know time series become non stationary.In Figure 2 values continuously fluctuate aroung a mean value that is zero.Also ups & downs fluctuate exhibit volatility clustering means high volatility follow high volatility and low volatility follow low volatility.Which is consistent with H.Kaur(2004).

Figure 1.

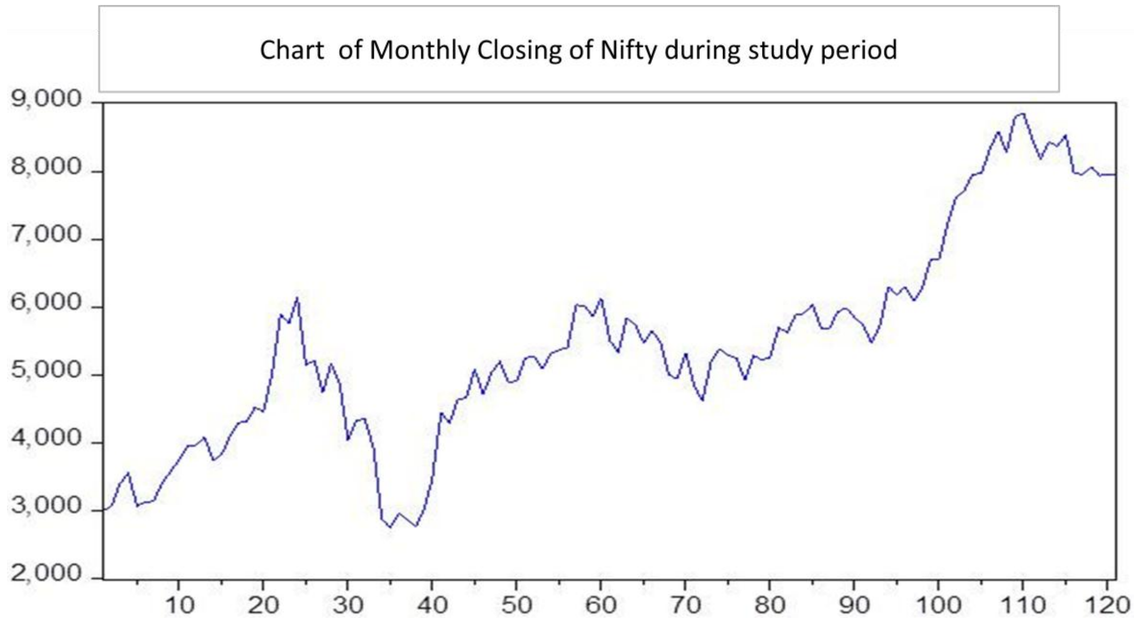
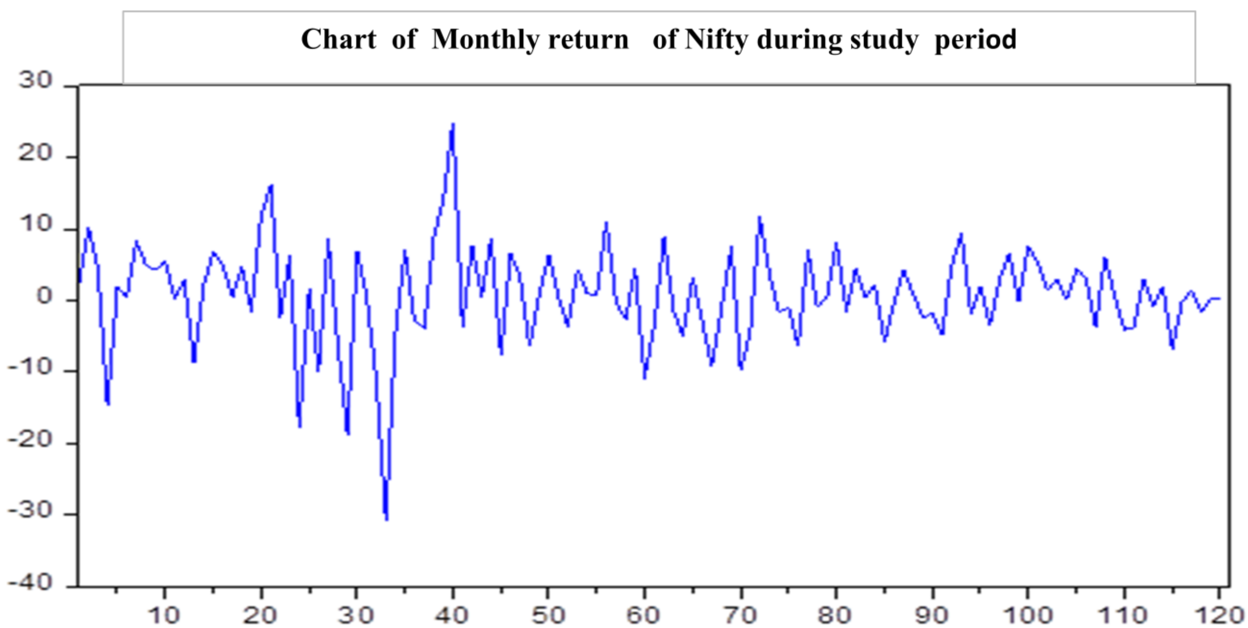


Figure 2.



Descriptive statistics of Nifty & Sensex return are shown in Table 1. Monthly mean return are positive and almost same for both indices. Nifty returns are negative skewed where Sensex returns are slight positive skewed. Which suggest that in both indices monthly returns are not symmetrical. Excess kurtosis value shows leptokurtic nature of return for both indices and close to mean and heavy tailed as compared to normal distribution. The Jarque-Bera statistics reject the normality hypothesis and this results confirms wellknown results about stock returns that they are not normally distributed & skewed.

Table.1 Descriptive Statistics of Nifty & Sensex returns

Procedure of Modeling :

GARCH (1,1) Model:

In an important things is that ARCH & GARCH models assumes conditional heteroscedasticity with homoscedastic unconditional error variance. Here variance is a function of past squared errors & past variance terms. The advantage of these models is that it captures volatility clustering and leverage effect.Estimation of GARCH (1,1) model : Following are the GARCH (1, 1) model. There parameter w, α ,β should be estimated. The model is

$$h_t = w + \alpha 1 \varepsilon_{t-1}^2 + \beta 1 \, h_{t-1}$$

Where w is constant , α is a ARCH parameter, β is a GARCH parameter .Now estimated GARCH (1, 1) model are as follows

$$h_t = 0.1668 + 0.123147 \varepsilon_{t-1}^2 + 0.8726 \, h_{t-1}$$

A large value of GARCH coefficient β_1 indicate that shocks to conditional variance takes a long time to die out, so volatility is ‘persistent. If ARCH coefficient α_1 relatively high as compared to β_1 tends to volatility “spicy”. But, generally The estimates of β*1* are always markedly greater
than those of α1 and the sum β1 + α*1* is very close to but smaller than unity. Here, sum of $\alpha_1 + \beta_1$ is equal to 0.9957 less than unity , indicating no violation of stability condition. The sum is close to one which indicate persistence of volatility for long time. After Fitting GARCH (1,1) model , validation of model diagnostic testing of residuals is required.Diagnostic testing for GARCH (1,1) model: To know GARCH(1,1) model best fit or not residual diagnostic testing is required.**LJung box (Q^2)** statistics detect serial correlation among residual terms. Following are the Correlogram of squared of residual.

H_0 : There is no serial correlation in standard squared residual terms

Statistic	**Nifty**	**Sensex**
Average	2.4355	2.4554
Standard Deviation	12.38569	12.66667
Skewness	-0.21	0.04
Excess Kurtosis	1.34	2.14
Median	2.066929	1.95406
Minimum	-28.1496	-28.7476
Maximum	35.09718	40.07219
Q1	-3.48338	-3.84968
Q3	11.11791	10.78195

Squared Residual Q^2 Correlogram

Date: 12/10/17 Time: 21:56
Sample: 1 121
Included observations: 120

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.057	-0.057	0.3991	0.528
		2	-0.081	-0.085	1.2156	0.545
		3	0.018	0.009	1.2574	0.739
		4	0.093	0.088	2.3397	0.674
		5	0.029	0.043	2.4471	0.784
		6	-0.051	-0.033	2.7844	0.835
		7	0.104	0.103	4.1806	0.759
		8	0.059	0.057	4.6334	0.796
		9	0.144	0.168	7.3727	0.598
		10	-0.109	-0.080	8.9483	0.537
		11	0.008	0.004	8.9568	0.626
		12	0.054	0.016	9.3556	0.672
		13	0.035	0.025	9.5275	0.732
		14	-0.109	-0.110	11.163	0.673
		15	-0.089	-0.104	12.270	0.658
		16	0.063	-0.019	12.836	0.685
		17	-0.004	-0.017	12.839	0.747
		18	-0.106	-0.109	14.461	0.699
		19	-0.045	-0.025	14.754	0.738
		20	0.134	0.100	17.383	0.628
		21	-0.115	-0.101	19.342	0.563
		22	-0.034	0.021	19.510	0.614
		23	-0.041	-0.009	19.767	0.656
		24	-0.060	-0.073	20.315	0.679
		25	-0.041	-0.052	20.576	0.716
		26	-0.072	-0.045	21.373	0.722
		27	0.070	0.085	22.139	0.730
		28	-0.091	-0.093	23.461	0.710
		29	0.106	0.087	25.266	0.664
		30	-0.041	0.030	25.543	0.698
		31	0.054	0.092	26.031	0.720
		32	-0.049	-0.049	26.426	0.744
		33	-0.012	0.013	26.448	0.783
		34	-0.022	-0.024	26.531	0.816
		35	-0.007	0.010	26.540	0.847
		36	0.118	0.049	28.979	0.791

*Probabilities may not be valid for this equation specification.

Here p value for all 36 lags grater than 0.05 which accept Hypothesis that there is no serial correlation in standard squared residuals. This is positive sign for model.

H_0 : There is no ARCH effect in Residual terms

Arch LM test

Heteroskedasticity Test: ARCH

F-statistic	0.383333	Prob. F(1,117)	0.5370
Obs*R-squared	0.388612	Prob. Chi-Square(1)	0.5330

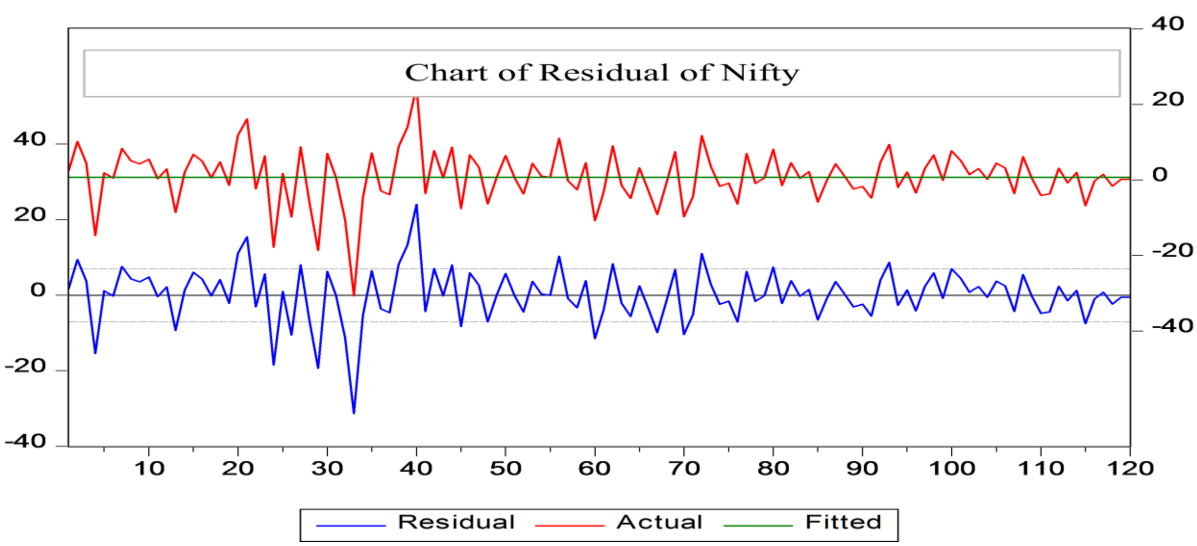
Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/10/17 Time: 22:00
Sample (adjusted): 2 120
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.079623	0.179158	6.026110	0.0000
WGT_RESID^2(-1)	-0.057152	0.092309	-0.619139	0.5370

R-squared	0.003266	Mean dependent var	1.021240
Adjusted R-squared	-0.005253	S.D. dependent var	1.657413
S.E. of regression	1.661761	Akaike info criterion	3.870297
Sum squared resid	323.0895	Schwarz criterion	3.917004
Log likelihood	-228.2826	Hannan-Quinn criter.	3.889263
F-statistic	0.383333	Durbin-Watson stat	1.997858
Prob(F-statistic)	0.537029		

Here p value is greater than 0.05 which indicate acceptance of Hypothesis. So there is no arch effect in residual. This is positive sign of model. Goodness of model is appropriate.Following figures for residual terms which reverting around mean and high volatility follow high and low volatility follow low which indicate volatility clustering.

Figure 3:



Asymmetrical or Leverage Effect : As Good result obtained from GARCH(1,1) model, one important feature of data can not obtained. This is asymmetrical or leverage effect. Generally return & volatility have negative correlation. Impact of bad news more on conditional volatility as compared to good news with same magnitude. This is known as asymmetric or leverage effect. Schwert (1989), French, Schwert &

Stambagh (1987) has observed this result. Nelson (1991) & Zakoivan(1994) found model which reflect above both impact. The model were EGARCH, TGARCH model. In TGARCH (1,1) model,

Following table shows symmetric as well as asymmetric effect on volatility.

Table 2: Symmetric & Asymmetric effect on conditional volatility of Nifty

Co efficient	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)
W constant	0.1668	-0.2294	0.099
α- ARCH	0.1231	0.28	0.1322
β-GARCH	0.8726	0.99	0.8732
α + β	0.9957	-	-
γ-Leverage	-	0.03	-0.015
Log likelihood	-391.93	-391.79	-3.91.92
AIC	6.59	6.61	6.61
SBC	6.69	6.72	6.73
Durbin-Watson	1.90	1.90	1.90
No.of Observation	120	120	120

In above table sum of ARCH & GARCH coefficient for GARCH(1,1) model is less than unity which shows long persistent of volatility and stability of model. But in both EGARCH(1,1) & TGARCH(1,1) model leverage coefficient does not show leverage effect. Both values are other than zero so there is a asymmetric effect found.AIC & BIC are highest & LLF is lowest as compared to GARCH (1,1) model .

7. CONCLUSION: In this paper GARCH(1,1) model is estimated. To check model's goodness of fit LJungbox's(Q) statistic, ARCH LM test, Jarque-Bera test used. The result of these test are positive for this model. In this study volatility clustering observed, means high volatility follow high volatility and low volatility follow low volatility which can be observe in Figure 2. Total of coefficient of ARCH & GARCH ($\alpha + \beta = 0.9957 < 1$) less than unity which shows volatility die out long time means volatility is persistence. Leverage effect captures through EGARCH or TGARCH model . Leverage effect means impact on conditional volatility of shocks not same, means impact of bad news(shocks) higher than impact of good news (shocks) on volatility. This leverage effect could not observed in volatility of nifty return but volatility is asymmetric in nature. The value of leverage coefficient $\gamma \neq 0$ means effect is asymmetric not symmetric.

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Prof. Vijay Kumar H. Raval
Associate Professor in Statistics
Gujarat Commerce College
Ahmedabad

Prof. G. C. Bimani
Head
Department of Statistics
Saurastra University
Rajkot