Volume : 2 | Issue : 2 | Feb 2013 • ISSN No 2277 - 8179

Research Paper

Management

KEYWORDS : Conditional Heteroskedasicity, ARCH/GARCH Models, Clustering, Persistence, Leverage Effect

Empirical Analysis of Stock Return Volatility by Using Arch-Garch Models: The Case of Indian Stock Market

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ABSTRACT

The Auto Regressive Conditional Heteroskedasicity (ARCH) effect is present in the stock return series during the study period. Therefore, the conditional variance is modeled with the ARCH/GARCH models. Indian stock market is highly volatile and there is existence of high level of persistence of shocks in volatility. Asymmetric volatility effect is present in all the indices under consideration. The study also demonstrates that there are significant leverage effects in the market. The investors in the market are relatively less mature and they are heavily influenced by information (good or bad) very easily. Indian stock market volatility is more sensitive to the bad news as compared to the good news. Besides, EGARCH (1,1) model appears to more appropriately represent the data of stock returns in all the four indices compared to GARCH (1,1) and TARCH (1,1) models.

Introduction:

Stock return volatility has received substantial interest from researchers, practitioners and policy makers in recent years. For, volatility is a measure of risk, hence affects the investor's aptitude towards investment. Moreover, degree of volatility affects the smooth functioning of stock markets and its high levels may smash the investor's confidence and risk taking ability. In recent years, with the introduction of neo-liberal policy regimes and more integration to the world economy in developing economies, the level of volatility is expected to be much higher. Thus, a study on stock market volatility is very essential in a developing country like India.

It has been established in the literature that stock market returns volatility is time varying, time dependent and follows the time varying dynamic process or heteroscedastic property. Many researchers have provided evidence concerning this characteristic of stock return volatility using the class of ARCH/GARCH models. Moreover, stock return volatility is highly persistent, especially in developing markets.

To capture the volatility in financial time-series, several models of conditional volatility have been proposed. An outstanding class of model was first introduced by Engle (1982) which was known as the ARCH (autoregressive conditional heteroskedasicity) model. This model was later generalized by Bollerslev (1986) to GARCH (generalized ARCH) model by including the lags of conditional variance itself. In these models, one very common finding in the financial asset is that shocks to volatility are often highly persistent.

Stock market volatility affects economic growth (Levine and Zervos, 1996 and Arestis et al 2001) and business environment (Zuliu, 1995). High stock market volatility indicates higher risk levels of equity investment, hence, transfer of funds from equity to debt. Researchers have investigated the causes of volatility, and found new, unexpected information affect expected returns (Engle and Mcfadden, 1994).

In India, meagre attempts have been made in this context, Roy and Karmakar (1995) investigates the heteroskedastic behavior of the Indian stock market using 'vanilla' GARCH (1, 1) model for a period of about 24 years from January 1980 to June 2003. The study reports an evidence of time-varying volatility which exhibits clustering, high persistence and predictability. Conditional volatility shows a clear evidence of volatility shifting over the period where the level of volatility for the decade nineties is considerably higher than that of the decade of eighties. Though the gradual shift of volatility started in response to strong economic fundamentals, the real cause for abrupt movement appears to be the imperfection of the market. Goyal (1995) used conditional volatility estimates, as recommended by Schwert (1989), to spot the trends in volatility. He also analyzed the impact of carry forward system on the intensity of volatility. ARCH/GARCH models have been used by Pattanaik & Chatterjee (2000) and Kaur (2004) to model volatility in the Indian financial markets and reached almost the same inference. Pradahan & Mall (2011) studied the volatility of India's stock future market, provided the evidence of high persistence of time varying volatility and its asymmetric effects. There is evidence of the presence of long memory in volatilty of all the index returns in indian stock market (Hiremath & Kamaiah, 2010).

This paper empirically investigates the dynamics of volatility in the Indian stock market. The study attempts to ascertain the evidence of time varying volatility in daily returns in major stock market indices of national stock exchange. Nature of volatility process has also been examined.

After giving brief introduction and literature review in the section-1, section-2 is deveoted to develop the methodolgy to study the stock return behaviour. Results and cosequent discussion is the part of section-3. The concluding remarks are presented in the last section.

(2) Research Methodology:

This study spanned the period from January 1, 2006 to July 31, 2011. During this period, Indian stock market has witnessed tremendous growth. In spite of world financial crisis, slow down and debt crisis in many European economies, Indian economy has registered significant growth. FII and DII have shown keen interest in Indian stock market, volatile behaviour of the stock market expected to be obvious consequence.

The sample population of the study consists of daily returns of the four most prominent indices in the National Stock Exchange namely CNX-Nifty, CNX-100, CNX-200 and CNX-500. Daily closing prices of the indices are considered for the study. Daily stock prices have been converted into daily returns. The data is collected form the official website of national stock exchange. The present study uses the logarithmic difference of two successive periods for the calculation of rate of returns. The logarithmic difference is symmetric between up and down movements and is expressed in percentage terms to facilitate comparison with the basic idea of percentage change.

If 'It' be the closing level of index under consideration on date t and 'It-1' be the same for its previous business day, i.e. exclude intervening weekend and stock exchange holidays, then the one day return on the market portfolio is calculated as:

$$r_t = (\log I_t - \log I_t\text{-}1) \times 100$$

ARCH-GARCH Models:

The existence of Heteroskedasicity has been established in the studies of financial markets (Mandelbrot, 1963; Fama, 1963; Bollerslav, 1986). These studies have found that stock return data indicates that successive returns are not independent rather in such data serial correlation is present. Moreover, existence of serial correlation in the squares of returns further highlights the high volatility and volatility clustering. Negative asymmetry in the distribution of returns questions the assumption of an underlying normal distribution. Leptokurtosis is the distribution of returns with too many values near the mean and tails of the distribution when compared with the normal distribution.

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In econometric literature, volatility clustering is modeled as an ARCH process. Robert Engle (1982) in his seminal work on inflation in the UK first introduced the idea of ARCH effect. Later on, Bollerslev (1986) generalized this type of model and introduced the GARCH model. Subsequently, many variants of the GARCH model have been proposed in the literature.

The ARCH and the GARCH models assume conditional heteroskedasicity, with homoscdasticity 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 as might be the case when using daily data. 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. Thus, unless information remains constant, which is hardly the case, volatility must be time varying even on daily basis.

In the financial market literature, GARCH class models are popular in capturing the dynamics of capital market volatility. For initial volatility estimation the GARCH (1,1) model is used, developed by Bollerslev. The model for returns is specified as under:

Mean Equation: $rt = c + \varepsilon t$

Variance Equation: $\sigma_t 2 = \omega + \alpha 1 \varepsilon^2 t\text{-}1 + \beta 1\ \sigma_{t-1}^{\ 2}$

GARCH (1,1) model assumes that the effect of a return shock on current volatility declines geometrically overtime. This model is consistent with the volatility clustering where large changes in the stock returns are likely to be followed by the further large changes.

In the standard GARCH model, it is assumed that only the magnitude of the shock, not the positivity or negativity of the shock, determine the volatility. Hence, GARCH process generates a symmetric response function for the stock returns. This suggests that separate modeling technique need to be used to capture the asymmetry in the response function.

EGARCH Model:
Asymmetric volatility is not captured by GARCH (1,1) model, hence, Nelson's Exponential GARCH (1,1) model for stock returns volatility estimation. In the EGARCH model, the mean and variance specifications are:

Mean Equation: $rt = c + \varepsilon t$

Variance Equation: $\log \sigma t^2 = \omega + \beta 1 \log \sigma_{t-1}^{\ 2} + \alpha 1 \left| \varepsilon t\text{-}1 / \sigma t\text{-}1 \right| + \gamma\ (\varepsilon t\text{-}1 / \sigma t\text{-}1)$

The left hand side of the model is 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 non-negative. The impact is asymmetric if $\gamma \neq 0$.

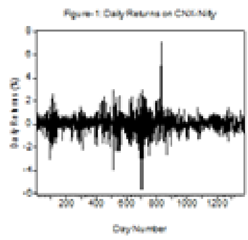
TGARCH Model:
Though the existence of the asymmetry in volatility can be checked in EGARCH model, however, on the basis of this model we can not say whether good news or the bad news that increase the volatility. This impact of volatility modeling is captured by Threshold GARCH model independently developed by Glosten, Jaganathan and Runkle (1994). The specification for conditional variance in TGARCH (1,1) model is:

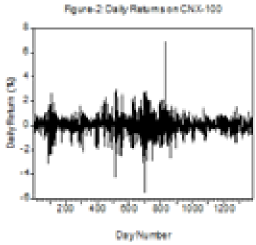
Mean Equation: $rt = c + \varepsilon t$
Variance Equation: $\sigma t^2 = \omega + \alpha 1 \varepsilon^2 t\text{-}1 + \beta 1\ \sigma_{t-1}^{\ 2} + \theta \varepsilon^2 t\text{-}1\ dt\text{-}1$
Where $dt\text{-}1=1$ if $\varepsilon t<0$, and $d_{t-1}=0$ otherwise

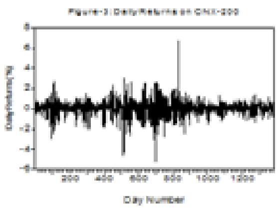
In this model, good news ($\varepsilon t<0$), and bad news ($\varepsilon t>0$), have differential effect on the conditional variance-good news has an impact of $\alpha 1$ and bad news has an impact of $\alpha 1+\theta$. If $\theta>0$, we say that leverage effect exists and if $\theta \neq 0$, the news impact is asymmetric.

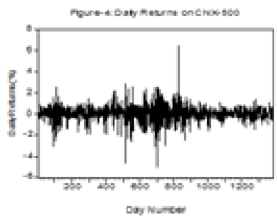
To estimate aforesaid models and diagnostic statistics advanced econometric package 'EViews' has been used.

(3) Results and Discussion:
Visual inspection of the plots of daily returns on CNX-Nifty, CNX-100, CNX-200 and CNX-500 are shown in the following figures.









It can be seen from the figures that returns continuously fluctuate around mean value that is close to zero. The movements are in the positive as well as negative territory and larger fluctuations tend to cluster together separated by periods of relative calm. This is consistent with Fama's (1965) observation that stock returns exhibit volatility clustering where large returns tend to be followed by large returns and small returns leading to adjacent periods of volatility and stability.

Descriptive statistics on the selected indices returns are summarized in Table-1. For all the indices returns, the Skewness statistic for daily returns is found to be different from zero indicating that the returns distribution is not symmetric. Furthermore, the relatively large excess kurtosis suggests that the underlying data is leptokurtic or heavily tailed and sharply peaked about the mean when compared with the normal distribution. The large Jarque-Bera statistic calculated to test the null hypothesis of normality rejects the normal assumption. The results confirm the well known fact that daily stock returns are not normally distributed but are leptokurtic.

Table-1: Descriptive Statistics of Daily Returns (January 1, 2006 – July 31, 2011)

Statistic	CNX-Nifty	CNX-100	CNX-200	CNX-500
Mean	0.02068	0.02076	0.01873	0.01833
Median	0.04933	0.05817	0.0704	0.0707
Maximum	7.0939	6.9233	6.7241	6.5291
Minimum	-5.6519	-5.4913	-5.1933	-5.0344
Standard Deviation	0.8143	0.8145	0.7973	0.7850
Skewness	0.0023	-0.0731	-0.1704	-0.2189
Excess Kurtosis	7.1692	6.8342	7.0295	6.8198
Jarque-Bera Statistic	2963.20*	2694.68*	2856.26*	2693.16*
Q(1)	3.6323*	5.5910*	11.153*	12.936*
Q(15)	17.0050*	27.956*	34.807*	36.355*
Q2(1)	19.309*	25.717*	37.264*	4.405*
Q2(15)	317.85*	337.23*	332.18*	345.28*
ARCH-LM	16.9579*	21.5390*	29.5399*	31.5857*
No. of Observations	1384	1384	1384	1384

* indicates the significant Values

Q(k) is the Ljung Box statistic identifying the presence of auto-correlation in the returns. Under the null hypothesis of no auto-correlation, it is distributed as $\chi 2(k)$.

Q2(k) is the Ljung Box statistic identifying the presence of auto-correlation in the squared returns. Under the null hypothesis of no auto-correlation, it is distributed as $\chi 2(k)$.

ARCH-LM statistic is Langrange Multiplier test statistic for the presence of ARCH effect.

All the indices appear to have strong autocorrelation with significant Q coefficient. Also, the autocorrelation in the squared daily returns suggests that there is clustering of variance. Highly significant value of Ljung-Box-Pierce Q statistic confirms the presence of first order autocorrelation in the return series and negates random walk behaviour. The above findings indicate the possible presence of ARCH effect which is confirmed by the computed value of ARCH-ML. Significant values for this statistic shows the clustering effect in daily returns i.e. large shocks to the error process are followed by large ones and small shocks by small ones of either sign.

Table-2: Unit Root Testing of Daily Returns
Augmented Dickey-Fuller Tests Number of Lags=100

Null Hypothesis	Test Statistic				MacKinnon Critical Value @ 5% level of significance
	CNX-Nifty	CNX-100	CNX-200	CNX-500	
Without Drift	-3.001	-2.965	-2.957	-2.942	-1.9396
With Drift	-3.063	-3.0241	-3.002	-2.985	-2.8642

Phillips-Perron Tests Truncation Lags=7

Null Hypothesis	Test Statistic				MacKinnon Critical Value @ 5% level of significance
	CNX-Nifty	CNX-100	CNX-200	CNX-500	
Without Drift	-37.172	-37.181	-37.169	-37.176	-1.9396
With Drift	-37.183	-37.182	-37.173	-37.179	-2.8642

Stationarity of the all indices return series are tested by conducting Augmented Dickey-Fuller and Phillip-Person tests. The results of both the tests for all indices returns confirm that the series are stationary for both with and without drift random walk (Table-2).

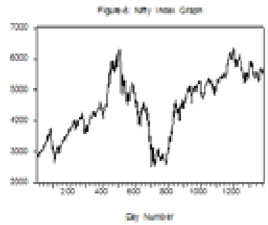
Results of CNX Nifty:
To study the dynamics of stock market volatility GARCH (1,1) model is used for initial estimation. The results of estimation of the GARCH (1,1) model are reported in table-3. All the coefficients in the GARCH (1,1) are significant. The estimate of $\beta 1$ is markedly greater than those of $\alpha 1$ i.e. bulk of the information comes from the previous days forecast (0.8577). The new information changes this little. The sum $\alpha 1+ \beta 1$ is very close to but smaller than unity (0.9923), and is useful for the purpose of forecasting conditional variance. As for the Stationarity of the variance process, as the sum is less than one, there is no violation of the stability condition.

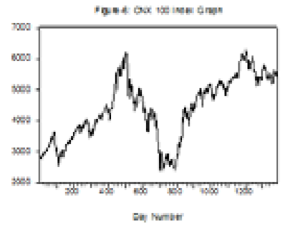
Table-3: Results of CNX Nifty

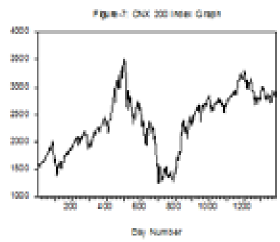
Coefficient	GARCH (1,1)	TARCH (1,1)	EGARCH (1,1)
ω	0.1033*	0.0119*	-0.2302*
$\alpha 1$	0.1346*	0.0598*	0.2639*
$\beta 1$	0.8577*	0.8526*	-0.1209*
$\alpha 1 + \beta 1$	0.9923		
θ (Resid<0)*ARCH(1)		0.1523*	
γ			0.9630*
Log Likelihood	-1433.92	-1421.95	-1417.26
Akaike info criterion	2.0808	2.0645	2.0582
Schwarz criterion	2.0997	2.0872	2.0809

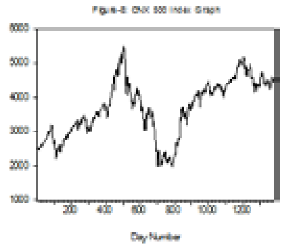
* indicates significant Values

However, the sum close to one indicates the long persistence of shocks in volatility. Poterba and Summers (1986) have argued that for a long period, persistence of shocks is needed to be able to explain the time varying risk premium. The reason for such an argument is that if shocks to the variance is transitory in nature i.e. has only short term effect, investors will not make any changes in their discounting factor while obtaining the present discounted value of the stock and hence its price.









There is an interesting feature in the graph of figure given above that the volatility is higher when prices are falling than when the prices are rising. It means that the negative returns are more likely to be associated with greater volatility than positive returns. This is called asymmetric volatility effect. And this can not be captured by GARCH (1,1) model. Hence, Nelson's Exponential GARCH (1,1) model for stock return volatility estimation is used. Since the value of γ is non zero (Table-3), the EGARCH model supports the existence of asymmetry in volatility of stock returns. All the coefficients are significant; the leverage term is statistically different from zero indicates the existence of the leverage effect for the stock market returns during the sample period.

But on the basis of this model it can not be inferred that whether good news or bad news that increases the volatility. This type of volatility modeling is captured by TGARCH model. In this model, good news has an impact of $\alpha 1$, while the bad news has an impact of $\alpha 1+ \theta$. If $\theta>0$, then bad news increases volatility. The figures given in the table-3 shows that the good news has an impact of 0.0598 magnitudes and the bad news has an impact of 0.2121 (0.0598 + 0.1523) magnitudes in the nifty returns. This can be inferred here that nifty index experiences substantial increase in volatility by the bad news.

The analysis shows better performance of the EGARCH model in estimating and predicting the market volatility. Hence we can say that the EGARCH model outperform the GARCH and TARCH models. This is based on the information provided by highest log likelihood, lowest AIC and SC. The improvements in the model fitting signify the fact that returns respond differently to the arrival of negative and positive shocks.

CNX-100:
Test has confirmed the presence of ARCH effect in the CNX-100 series. Hence, ARCH-GARCH models are used to model the behaviour of stock returns in CNX-100 index. The results of such estimation are presented in the table-4. From this table it can be seen that EGARCH model has the largest log likelihood and smaller AIC and SC, hence, considered as the superior model than the others. In addition, when the study used GARCH (1,1) to estimate the data $\alpha 1+ \beta 1$, its value turned out to be 0.9941, this is very close to one. This demonstrates that there is high durability of the volatilities that is if there is an expected shock in these markets, the sharp movement will not die out in the short-run. This is a sign of high risk. At the same time, the summation of the parameters is less than one, which indicates that

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GARCH process for the stock return is wide-sense stationary. In the EGARCH model γ turned out to be non-zero i.e. EGARCH model supports the existence of asymmetry in volatility of stock returns.

When the data of CNX-100 is exposed to the TARCH model, it is found that estimate of θ is greater than 0. Moreover, the conditional volatilities caused by the positive shocks (.0598) are considerably smaller than the volatilities caused by the negative shocks 0.2095 (.0598 + 0.1497). This is consistent with the most existing literature.

Table-4: Results of CNX-100

Coefficient	GARCH (1,1)	TARCH (1,1)	EGARCH (1,1)
ω	0.0098*	0.0109*	-0.2265*
α1	0.1385*	0.0598*	0.2639*
β1	0.8556*	0.8564*	-0.1211*
α1 + β1	0.9941		
θ (Resid<0)*ARCH(1)		0.1497*	
γ			0.9647*
Log Likelihood	-1423.764	-1411.320	-1405.906
Akaike info criterion	2.0676	2.0511	2.0432
Schwarz criterion	2.0866	2.0738	2.0659

· indicates significant Values

CNX-200 and CNX-500:

To have a better understanding of stock market behaviour, data CNX-200 and CNX-500 has also been analyzed. Its results are shown in the table-5 and table-6. It is evident from the ARCH-LM test that the ARCH effect is present in the returns of both the markets. Hence, ARCH-GARCH model is used to model the conditional variance. The results of these models are presented in the table-5 and table-6. All the variables of the variance equations are significant for the returns in the two markets. GARCH (1,1) model indicates that α1+ β1 for both the markets are 0.9959 and 0.9969, very close to one. It reveals that there high persistence of the volatilities in both the markets. Hence, high risk is involved in the performance of such markets. In addition the summation of parameters is less than one which indicates that the GARCH process for the stock returns indicates stability. In both the markets the EGARCH model seems to be best fit taking into consideration the log likelihood and AIC and SC values. In the EGARCH model γ turned out to be non-zero i.e. EGARCH model supports the presence of asymmetry in volatility of both markets. Moreover, the significant value of γ in both the tables shows the existence of the leverage in both markets.

Table-5: Results of CNX-200

Coefficient	GARCH (1,1)	TARCH (1,1)	EGARCH (1,1)
ω	0.0093*	0.0104*	-0.2359*
α1	0.1443*	0.0601*	0.2702*
β1	0.8516*	0.8550*	-0.1213*
α1 + β1	0.9959		
θ (Resid<0)*ARCH(1)		0.1487*	
γ			0.9627*
Log Likelihood	-1385.286	-1372.893	-1367.245
Akaike info criterion	2.0105	1.9940	1.9858
Schwarz criterion	2.0294	2.0167	2.0085

· indicates significant Values

Table-6: Results of CNX-500

Coefficient	GARCH (1,1)	TARCH (1,1)	EGARCH (1,1)
ω	0.0086*	0.0095*	-0.2352*
α1	0.1435*	0.0614*	0.2694*
β1	0.8534*	0.8576*	-0.1165*
α1 + β1	0.9969		
θ (Resid<0)*ARCH(1)		0.1423*	
γ			0.9643*
Log Likelihood	-1359.760	-1347.995	-1341.835
Akaike info criterion	1.9750	1.9594	1.9505
Schwarz criterion	1.9939	1.9821	1.9732

· indicates significant Values

When the data of CNX-200 & CNX-500 is exposed to the TARCH model, it is found that estimate of θ is greater than 0 in both the markets. Moreover, the conditional volatilities caused by the positive shocks (0.0601, 0.0614) are considerably smaller than the volatilities caused by the negative shocks 0.2088 (0.0601+ 0.1487) & 0.2037 (0.0614 + 0.1423). This is consistent with the most existing literature.

(4) Concluding remarks:

The study reveals that Indian stock market has significant ARCH effect in the stock return series and it is appropriate to use the ARCH-GARCH models to estimate the process. ARCH test is highly significant in all the indices under consideration. The values of α1+ β1 are close to one indicates the high level of persistence of shocks in volatility. So, Indian stock market is highly risky. Moreover, volatility is higher in the falling market as compared to rising market. Hence, asymmetric volatility effect is present in all the indices. The study also demonstrates that there are significant leverage effects in the market. The investors in the market are relatively less mature and they are heavily influenced information (good or bad) very easily. Indian stock market is highly volatile and it is more sensitive to the bad news as compared to the good news. Besides, EGARCH (1,1) model appears to better represent the data of stock returns in all the four indices compared to GARCH (1,1) and TARCH (1,1) models.

The overall scene in the entire market indicates that persistence effect is stronger in the much wider indices. Though asymmetric effect is present in the all markets but it is highest in the CNX-100 followed by CNX-500, Nifty and CNX-200. Volatility by the positive shocks is relatively stronger in more comprehensive indices (CNX-500, CNX-200) as compared to the other indices. Volatility in nifty is highly affected by the negative shock where as the affect of negative shock reduces as we go down to the more comprehensive indices.

Regulatory authorities should keep an eye on high volatility to protect the investors from the activities of speculators. Better surveillance on the volatility would help to build confidence among the investors. Moreover, the investors should be rational enough that they are not panicked by the temporary shocks.

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