Dynamics of Time Varying Volatility of Indian Stock Market : Evidence from BSE & CNX Nifty

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Abstract

Volatility measures the variability and ascertains the unpredictable and uncertain behavior of the asset price. As a concept and phenomenon, it has remained central area of research in modern financial markets and academics. The importance of volatility in stock market can't be undermined in financial economics, as it plays a significant role in investment and risk management decisions. This paper attempts to examine the dynamics of time varying volatility of Indian stock market with reference to BSE and S&P CNX Nifty. Using daily observation, data have been taken for period of 2000-2014. To examine the characteristics of Indian Stock Market Volatility, GARCH models are being employed. EGARCH and TARCH are employed to find possibility of Asymmetry or Leverage effects in the market.

Keywords: *Volatility, Financial Economics, GARCH, Asymmetry, Leverage effect, EGARCH, TARCH*

Introduction

Volatility as a basic statistical risk measure has been used both for market risk assessment of a single instrument or an entire portfolio. It may be calculated for all sorts of financial variables viz., interest rates, exchange rate, stock returns, market value of portfolio to name a few. We can simply say volatility is a conditional variance or standard deviation. Volatility of stock returns may be termed as conditional variance of the stock returns in time or standard deviation of stock return around the mean value. Investors rely on variance of returns changing over time to make optimal decisions regarding their investment strategies. So, it becomes imperative to model and forecast conditional variance. Volatility as a phenomenon as well as a concept has always acquired the centre stage to modern financial markets and academic fraternity as it forms the basis for efficient market discovery. Volatility measures the degree to which asset prices tend to fluctuate and thus ascertains

variability or randomness of asset price. Volatility may be termed as the measure of risks.

On reason behind volatility, there have been divergent views by various sections of economists. Some believe that market volatility can be explained entirely by the information provided to the market. They believe that every new information in the market has an impact on the market volatility. While other group of economists believes that any economic or external factor does not have an impact on market volatility. It is only the psychological or social belief of investors that influence the market volatility. Volatility may be termed as inevitable market experience as a result of

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close associations or interactions between fundamental economic forces, information and market expectations. In spite of controversy, ascertaining volatility trends or modeling of volatility help decide the efficient and effective investment strategies and portfolio management.

Review of Literature

Srinivasan and P. Ibrahim(2010) used GARCH class models ranging from Simple-GARCH (1,1) to relatively complex GARCH models like EGARCH and TGARCH for modeling the volatility and forecasting the conditional variance of BSE SENSEX-30

Aman Srivastava (2008) used GARCH- class models to two major Stock Exchanges of Indian Stock Market to analyze their characteristics of volatility and found significant ARCH effects. His study also demonstrated the existence of leverage and asymmetric effect in Indian Stock Market.

Madhusudan Karmarkar (2007) investigated the Heteroskedasticity behavior of Indian Stock Market by using different GARCH models. He investigated the asymmetric volatility in Indian Stock Market by employing EGARCH. Karmarkar found that volatility is asymmetric function of past innovation rising proportionatey more during market decline and was evidenced that return is not significantly related to risk.

Srinivasan et al (2010) used number of forecasting models like Random Walk, Linear Regression, Moving Average, Autoregressive models on NSE daily returns to evaluate the forecasting performance of the same. To evaluate the same, they used two forecasting error statistics by considering the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) for testing the return characteristics. The findings suggested that according to RMSE statistics the autoregressive models and Linear Models rationally shared and ranked first for out of the sample forecasts in the linear models. In addition, their findings also suggested that one cannot conclude that the success or failure of a particular type of forecasting model applied to one type of market carries over to different market because the size and liquidity of market can affect the quality of volatility forecasts.

R. Krishnan and Conan Mukherjee (2010) identified GARCH models best suitable for the Indian Stock Market Volatility by building models in the line of traditional GARCH method with asymmetry and nesting through Box-Cox Transformation- a family of GARCH models. Their results confirmed the presence of leverage effect in the stock market. They also showed that it is the smaller shocks that affect the returns in Indian Stock Market and dominate the news impact curve than the large shocks. Another typical feature they showed that on trading days, it has been found to be accounting for a sizeable portion of return variance contributing almost one fourth as much to volatility as any trading day.

Rakesh Kumar and Raj. S. Dhankar (2011) investigated the asymmetric nature of U.S.Stock Market return and effect of heteroskedasticity on stock return volatility. They also analysed the relationship between stock return and conditional volatility and standard residuals. Their study applied GARCH (1,) AND TAR-GARCH (1,) to test the heteroskedasticity and asymmetric nature of stock market returns respectively. The study suggested the presence of non lineariy, heteroskedasticity effect and asymmetric nature of stock ereturns. Their finding brought out the essential elements of modern investment theory that investors adjust their investment decision with respect to expected volatility. However, they tend to earn extra risk premium for unexpected volatility.

Sailesh Rastog and Vinay.k.Srivastava used time varying variance based GARCH process to capture change in volatility and study its mpact on Indian Securities Maret. Further they compared the change in volatility of Indian Stock Market with U.S.Stock Market.

M.Selvam et.al.(2007) investigated the dynamic behavior of Stock Return of ten market indices from Asian countries using symmetrc GARCH(1,1) model for a period of one year from January2006 to December 2006.

Sharmila Jayasuriya et.al.(2009) estimated equity market volatility using an asymmetric power GARCH model . The magnitudes of asymmetric volatility for several emerging and mature markets were estimated for three sub periods.

J.XU(1999) usng Shanghai daily stock returns data, studied the models for stock market volatility by comaparing GARCH, EGARCH, and GJR GARCH models. He found that the GARCH model accounting for time varying volatility is the suitable model.

Nicholas Apergis and Sophia Eleptherine (2001) investigated the volatility of Athens Stock excess reurns over the period 1990-1999 through the comparison of various conditional Heteroskedasticity models. The empirical results indicated that there is significant evience for asymmetry in stock returns which is captured by a quadratic GARCH specification model.

Saint Kuttu (2014) used multivariate VAR-EGARCH model to examine the return and volatility dynamics between their traded adjusted equity returns from Ghana, Kenya, Nigeria and South Africa. The findings suggested a reciprocal return spill over between Ghan and Kenya and between Nigeria and South Africa.

Prashant Joshi (2010) investgated the stock market volatility in emerging stock markets of India and China using daily closing price from 1st January 2005 to 12th May 2009. The results detected the presence of non-linearity through BDSL test while conditional heteroskedasticity was identified through ARCH-LM test. The findings revealed that the GARCH (1,) MODEL successfully captures the non linearity and volatility clustering.

Methodology of modeling the Volatility Trends

Financial time series like stock market returns have characteristics distinct from other economic series. They have a peculiar characteristics whereby large changes in series are followed by more large changes and small by small changes which is termed as Volatility Clustering. This is also turned as Autoregressive Conditional Heteroskedasticity (ARCH) in language of financial econometrics.

Volatility Clustering as a characteristic of equity returns also mirrors the Leptokurtic (fat tails) in returns distribution with too many values near the mean and in the tails of the distribution as compared to normal distribution. In such series, there lies a negative asymmetry in distribution of returns rather than normal distribution. The very objective of this paper is to examine the dynamics of time varying volatility of Indian stock market with reference to BSE SENSEX and CNX Nifty. The required daily return data are collected from official website of NSE, BSE and money control.com. GARCH class models viz. GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) have been employed to depict the capital market volatility and to produce evidence of time varying volatility.

General Auto Regressive Conditional Heteroskedasticity (GARCH)

For Volatility estimation, the GARCH (1,1) Model was proposed by Bollerslev (1986). The model for daily stock return is specified as under:

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

Variance Equation: $\sigma^2_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1}$

Since σ^2_t is the one period ahead forecast variance based on past information, it is called the conditional variance. The above specified conditional variance equation is a function of three terms : a constant term (ω), news about volatility from the previous period, measured as the lag of squared residual from the mean equation (ε^2_{t-1}), and the last period's forecast variance (σ^2_{t-1}). The GARCH (1,1) Model assumes that the effect of a return shock on current volatility decline geometrically over time. The model is consistent with the volatility clustering where large changes in stock returns are likely to be followed by further large changes. The amplitude of daily stock returns change in both the markets. The magnitude of this change is sometimes large and sometimes small and is termed Volatility Clustering which is measured by GARCH Model. Many times we witness that volatility is higher when prices are falling than when prices are rising which means that negative returns are more likely to be associated with greater volatility than positive returns. This is termed as asymmetric Volatility Effect which is not captured by GARCH(1,1) Model.

Exponential General Autoregressive Conditional Heteroskedasticity (EGARCH) model:

Nelson (1991) proposed Exponential GARCH Model which allows the conditional volatility to have asymmetric relation with past data. In EGARCH Model, the mean and variance specifications are:

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

Variance Equation:
$$\log(\sigma^2_t) = \omega + \alpha\log(\sigma^2_{t-1}) + \beta\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + Y\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The left hand side of above variance equation is the logarithm of the conditional variance. This implies that the leverage effect is the exponential and that the forecasts of the conditional variance are guaranteed to be non negative. In EGARCH model α is the GARCH term that measures the impact of last period's forecast variance. A positive α indicates volatility clustering implying that positive stock price changes are associated with further positive changes and the other way around. β is the ARCH term that measures the effect of news about volatility from previous period on current period volatility. β is the measure of leverage effect. The presence of leverage effect may be tested by the null hypothesis that the coefficient of the last term in regression is negative ($y<0$). The impact is asymmetric if this coefficient is different from zero. Ideally β is expected to be negative implying that bad news has a bigger impact on volatility than good news of equal magnitude. The sum of the ARCH and GARCH coefficients, i.e. $\alpha+\beta$ indicates the extent to which a volatility shock is persistent over time. The stationary condition is $\alpha+\beta<1$. Since the value of y is non zero, the EGARCH model supports the existence of asymmetry in volatility of stock returns.

Threshold General Autoregressive Conditional Heteroskedasticity (TGARCH) Model:

To ascertain whether good news or bad news increases volatility, TGARCH Model was developed independently by Glosten, Jaganathan and Runkle (1993) and Zakoian (1994).

The specification for conditional variance in Threshold GARCH (1,1) model is:

$$\sigma^2_t = \omega + (\alpha + yI_{t-1})\,\varepsilon^2_{t-1} + \beta_1\,\sigma^2_{t-1}$$

Here the dummy variable I_{T-1} s an indicator for negative innovations and is defined by : $I_{T-1} = 1$ if $\varepsilon_{t-1} < 0$ and $I_{T-} = 0$ if $\varepsilon_{t-1} > 0$. In this model, good news, $\varepsilon_{t-1} > 0$ and bad news $\varepsilon_{t-1} < 0$ have differential effects of on the conditional variance; good news has an impact of α, while bad news has an impact of $\alpha + y$. If $y > 0$, then bad news increases volatility, and we say that there is leverage effect. If $y \mp 0$, the news impact is asymmetric.

Finally, the best suited volatility model is choosen by assessing the information criteria viz minimum Akaike Information Criterion (AIC) minimum Bayesian Information Criterion and Schwartz Information Criterion (BIC or SIC) and maximum Log likelihood values.

Empirical Results and Discussions;

Descriptive Statistics of both BSE SENSEX and CNX Nifty show that mean is close to zero. High Standard Deviation of 0.0159 of both BSE SENSEX and CNX Nifty indicate high level of fluctuation in Index Returns. Negative value of skewness for both BSE SENSEX and CNX Nifty indicate asymmetric tail extending more towards negative values than positive one. The Kurtosis value of 7.98 and 6.82 for BSE SENSEX and CNX Nifty respectively is much higher than 3 indicating that the return distribution is fat tailed or Leptokurtic. The series for both BSE SENSEX and CNX Nifty is non normal according to Jarque Bera Test which rejects normality at 1% level.

Figure 1, 2, 3 and 4 represent the daily closing price of returns series for BSE-SENSEX and CNX Nifty respectively. The plots of BSE SENSEX and CNX Nifty closing prices indicate the presence of Random Walk and Volatility Clustering which implies that volatility changes over time. The L-Jung Box statistics Q (29) for the returns series are highly significant at 1% level which indicate the presence of Auto-Correlation. ARCH LM Test is employed to ascertain the evidence of ARCH effects and the same is also witnessed. The presence of volatility clustering could be attributed to high kurtosis values. Presence of ARCH effects justifies the use of GARCH type models for the conditional variance. Moreover, ADF test and KPSS test were employed to test the stationarity of return series and the results are shown in Table 1. The summary statistics of the return series best describes the unconditional leptokurtic distribution volatility clustering and possess significant ARCH effects.

Descriptive Statistics	BSE-SENSEX	NSE CNX Nifty
Mean	0.000426010	0.000422576
Median	0.00106308	0.00107693
Minimum	-0.118092	-0.130539
Maximum	0.159900	0.163343
Standard Deviation	0.0159994	0.0159324
Skewness	-0.171483	-0.279197
Kurtosis	6.82642	7.98624
Jarque Bera Test(Probability)	6801.31(0.000)	9317.35(0.000)
ADF Test (No Constant, No Trend)	-11.4971	-10.726
ADF (Constant)	-11.6031	-10.8459
ADF (Constant and Trend)	-11.6026	-10.8443
KPSS Test	0.121387	0.102052
Ljung Box (Q) Statistic	23.5255	23.9121
Sample Size	3494.00	3489.00

Table 1: Descriptive Statistics for Stock Returns for BSE SENSEX and CNX Nifty
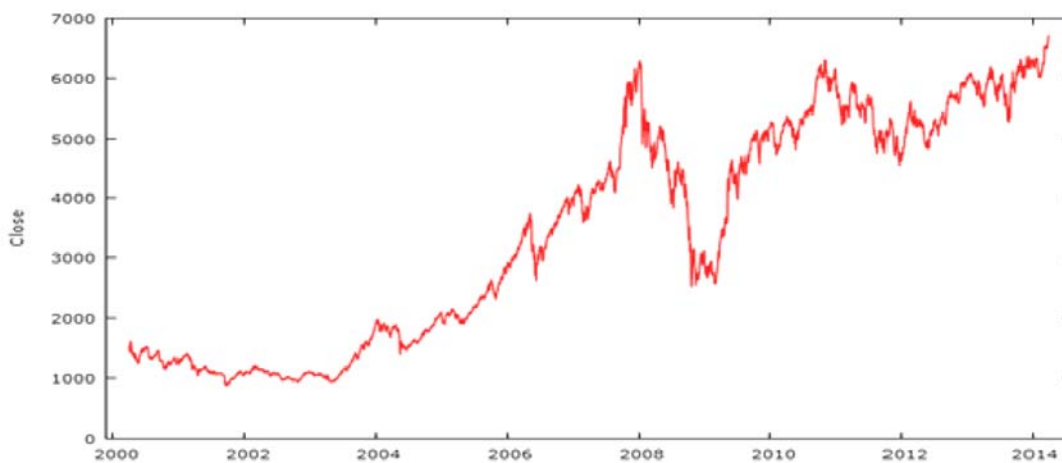

Figure 1:   Time Series Plot for Close Price of BSE-SENSEX from year 2000 to year 2014.
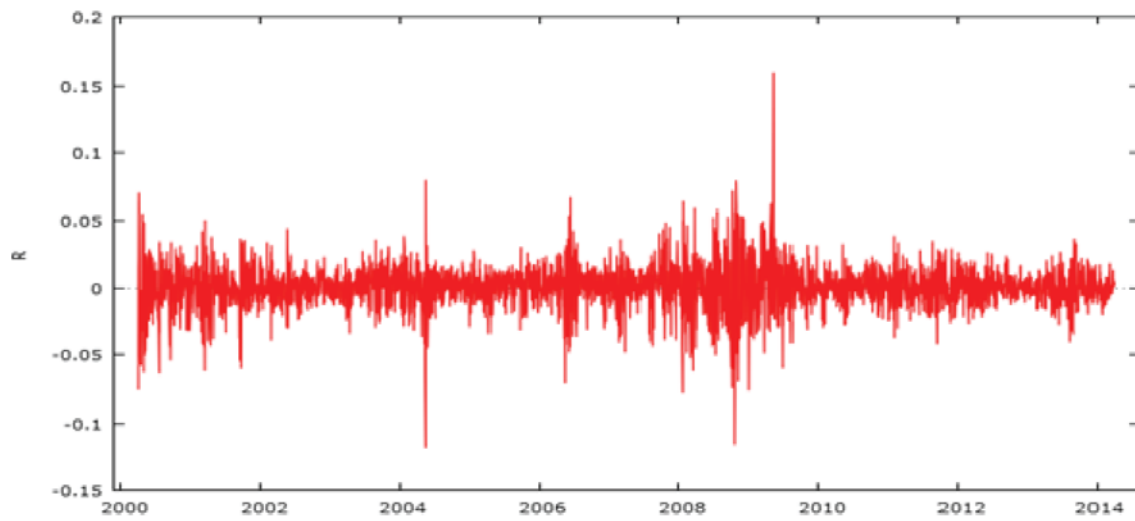
Figure 2: Time Series plot for Stock Returns for BSE SENSEX for year 2000 to year 2014.
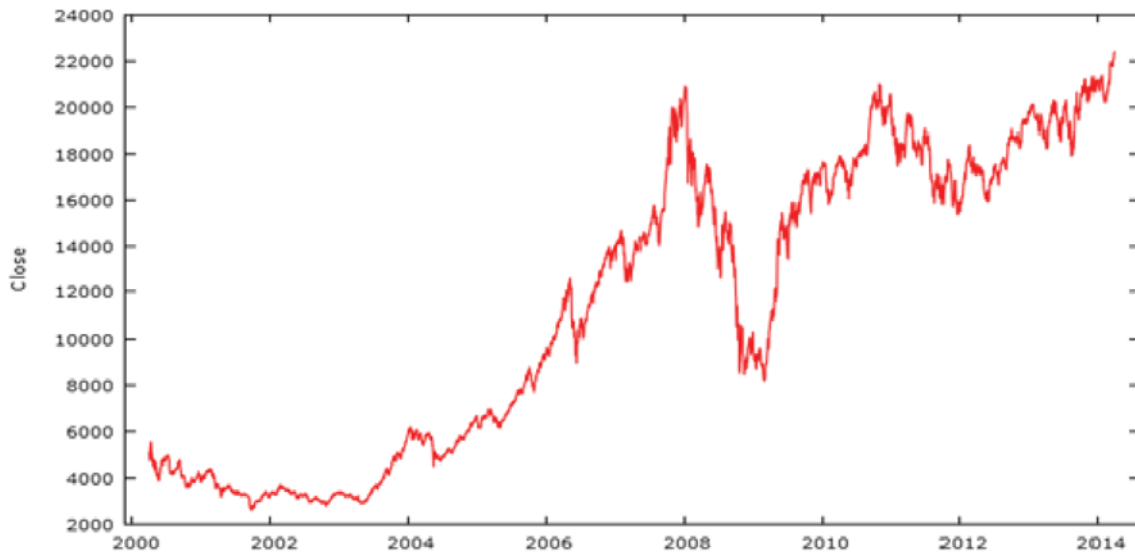

Figure 3: Time Series Plot for Daily Closing Price of CNX Nifty for year 2000 to year 2014
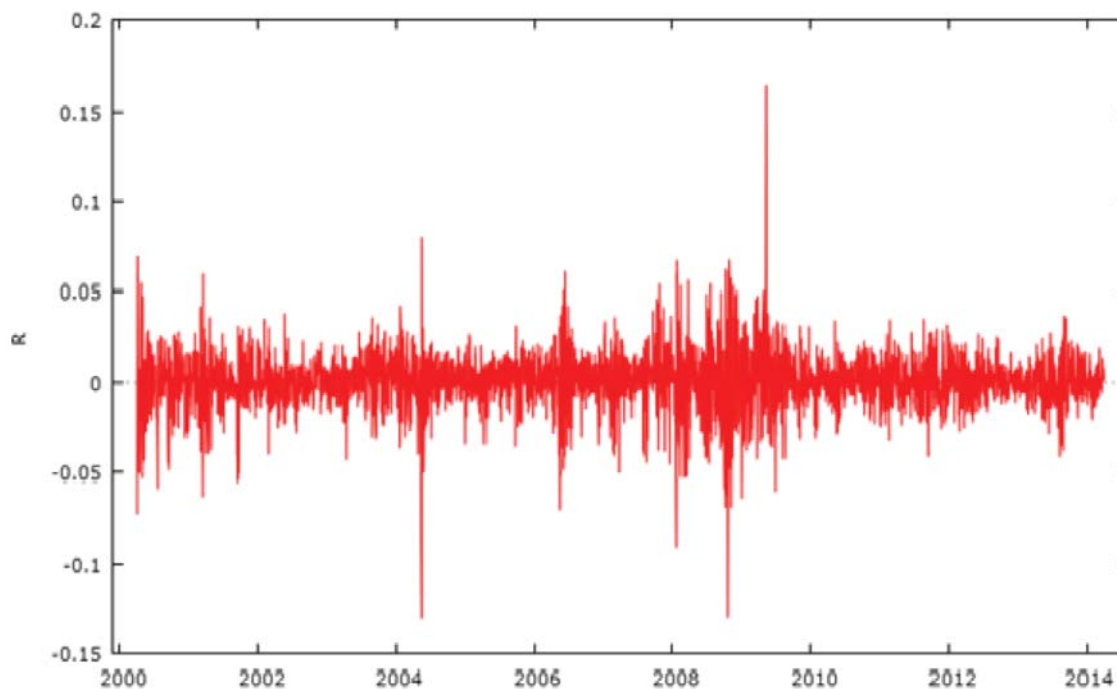
Figure 4: Time Series Plot for Stock Returns of CNX Nifty for year 2000 to year 2014.

Table 2 and 3 shows the estimates of GARCH (1,1), EGARCH (1,1) and TGARCH or TARCH (1,1) models for both BSE SENSEX and CNX Nifty respectively. Table 2 and 3 reveal that in case of GARCH(1,1) MODEL FOR BOTH BSE SENSEX and CNX Nifty the sum of ARCH and GARCH term i.e. $(\alpha+\beta)$ has been very close to one which indicates that the volatility shocks are very persistent and point towards the presence of covariance stationary model with high degree of persistence and long memory in the conditional variance. Here, it is clear that bulk of information come from previous day forecasts i.e. around 85% in case of both BSE SENSEX and CNX Nifty respectively. The new information changes this a little and the long run average variance has very small effect.

Table 2
GARCH(1,1), EGARCH(1,1) and TGARCH (1,1) Models for BSE SENSEX.
Model: GARCH(1,1) [Bollerslev] (Normal)*
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3494), VCV method: Robust

Conditional mean equation

	Coefficient	std. error	z	p-value
const	0.000975998	0.000215007	4.539	5.64e-06 ***

Conditional variance equation

	Coefficient	std. error	z	p-value	
omega	5.13537e-06	1.56004e-06	3.292	0.0010	***
alpha	0.126863	0.0199529	6.358	2.04e-010	***
beta	0.854089	0.0225750	37.83	0.0000	***

Llik: 10085.36258   AIC: -20162.72517
BIC: -20138.08996   HQC: -20153.93239

Model: EGARCH(1,1) [Nelson] (Normal)
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3489), VCV method: Robust

Conditional mean equation

	Coefficient	std. error	z	p-value	
const	0.000515389	0.000260221	1.981	0.0476	**

Conditional variance equation

	Coefficient	std. error	z	p-value	
omega	-0.473319	0.0845245	-5.600	2.15e-08	***
alpha	0.234332	0.0270768	8.654	4.96e-018	***
gamma	-0.0855040	0.0170656	-5.010	5.43e-07	***
beta	0.966079	0.00874092	110.5	0.0000	***

Llik: 10106.92574   AIC: -20203.85149
BIC: -20173.05748   HQC: -20192.86051

Model: TARCH(1,1) [Zakoian] (Normal)
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3494), VCV method: Robust

Conditional mean equation

	coefficient	std. error	z	p-value	
const	0.000515104	0.000214975	2.396	0.0166	**

Conditional variance equation

	coefficient	std. error	z	p-value	
omega	8.39995e-06	2.10843e-06	3.984	6.78e-05	***
alpha	0.128581	0.0156726	8.204	2.32e-016	***
gamma	0.395571	0.0754199	5.245	1.56e-07	***
beta	0.863816	0.0172745	50.01	0.0000	***

Llik: 10105.67131 AIC: -20201.34263
BIC: -20170.54861 HQC: -20190.35165

Table 3

GARCH(1,1), EGARCH(1,1) and TGARCH (1,1) Models for CNX Nifty
Model: GARCH(1,1) [Bollerslev] (Normal)*
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3489), VCV method: Robust

Conditional mean equation

	coefficient	std. error	z	p-value
const	0.000940610	0.000219153	4.292	1.77e-05 ***

Conditional variance equation

	coefficient	std. error	z	p-value
omega	5.54463e-06	1.75236e-06	3.164	0.0016 ***
alpha	0.126984	0.0209010	6.075	1.24e-09 ***
beta	0.853162	0.0234635	36.36	1.75e-289 ***

Llik: 10042.90591 AIC: -20077.81182
BIC: -20053.18234 HQC: -20069.02044

Model: EGARCH(1,1) [Nelson] (Normal)
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3489), VCV method: Robust

Conditional mean equation

	Coefficient	std. error	z	p-value
Const	0.000539504	0.000264441	2.040	0.0413 **

Conditional variance equation

	Coefficient	std. error	z	p-value
omega	-0.521224	0.0976176	-5.339	9.32e-08 ***
alpha	0.242385	0.0282976	8.566	1.08e-017 ***
gamma	-0.0921352	0.0184519	-4.993	5.94e-07 ***
beta	0.961150	0.0102844	93.46	0.0000 ***

Llik: 10069.08070   AIC: -20128.16139
BIC: -20097.37454   HQC: -20117.17217

Model: TARCH(1,1) [Zakoian] (Normal)
Dependent variable: R
Sample: 2000/04/04-2014/03/31 (T = 3489), VCV method: Robust

Conditional mean equation

	Coefficient	std. error	z	p-value
const	0.000540272	0.000214677	2.517	0.0118 **

Conditional variance equation

	Coefficient	std. error	z	p-value
omega	9.53577e-06	2.41702e-06	3.945	7.97e-05 ***
alpha	0.134023	0.0167241	8.014	1.11e-015 ***
gamma	0.414067	0.0764776	5.414	6.16e-08 ***
beta	0.855009	0.0186384	45.87	0.0000 ***

Llik: 10067.54609   AIC: -20125.09218

BIC: -20094.30533   HQC: -20114.10296

In case of EGARCH (1,1) the sum of ARCH and GARCH coefficients i.e. $(\alpha+\beta)$ indicates the extent to which a volatility shock is persistent over time. Here, since $(\alpha+\beta)$ for both BSE SENSEX and CNX Nifty have been greater than one i.e. 1.19 and 1.20 for BSE SENSEX and CNX Nifty respectively which point towards non stationary condition. Since $\gamma = 0$, EGARCH model supports the existence of asymmetry in the stock return. A negative value of γ i.e. -0.0855 and -0.092 for BSE SENSEX and CNX Nifty respectively shows that bad news has a bigger impact on volatility than good news of same magnitude.

In TGARCH or TARCH(1,1) model, the good news has an impact of $\alpha = 0.1285$ and $\alpha = 0.134$ on volatility of BSE SENSEX and CNX Nifty respectively. Bad news has an impact of $(\alpha + \gamma) = 0.51$ and 0.54 on the volatility of BSE SENSEX and CNX Nifty respectively.

Since $\gamma = 0$, it can be concluded that the news impact is asymmetric and there is presence of leverage effect. The Value of $(\alpha+\beta+\gamma/2)$ has been 1.190183 and 1.196066 for BSE SENSEX and CNX Nifty respectively which shows that the conditional variance is not stationary. On the basis of Akaike Information Criterion (AIC), Bayesian Information Criteron or Schwartz Information Criterion (BIC or SIC) and Maximum Likelhood ratio (Llik), EGARCH (1, 1) models is the most fitting model with minimum AIC, BIC or SIC and maximum Llik for both BSE SENSEX and CNX Nifty respectively.

Conclusion:

Forecasting and Modeling Volatility have become an important area of research in financial markets. Characteristics of Indian Stock Market Volatility have been similar to many other major developed and emerging stock markets. It has witnessed auto correlation and negative asymmetry in daily returns. It is shown that asymmetrical GARCH Models have outperformed symmetrical GARCH Models. As shown in EGARCH(1,1) and TARCH (1,1) Model, negative news have a greater impact on volatility of Indian Stock Market as comapred to good news of equal magnitude.The Conditional Variance in both BSE SENSEX and CNX Nifty has been non stationary.

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