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 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 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 look possibility of Asymmetry or Leverage effects in the market.

Keywords: *Volatility, Indian Stock Market, Financial Economics, Investment Risk Management divisions, GARCH, Asymmetry, Leverage effect, EGARCH, TARCH*

Introduction

Volatility as a basic statistical risk measure has been used to measure the market risk 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 concept has always acquired 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 measure of risk.

With regards to 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 have impact on market volatility. While other sections of economists believe that any economic or external factor does not have any 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 close association or interactions between fundamental, information and market expectation.

Ascertaining volatility trends or modeling of volatility aids in efficient and effective investment strategies and portfolio

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management. 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, and 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 among GARCH models that best describe the Indian Stock Market Volatility by building Volatility models using traditional GARCH models that account for asymmetry and selecting a suitable model by 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 that the large shocks. Another typical feature they showed that the on trading days 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 targarch (1,) to test the heteroskedasticity and asymmetric nature of stock market returns respectively. The study suggested the presence of non leariy, 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 based GARCH process to capture change in volatility and study its impact on Indian Securities Maret. 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 January 2006 to December 2006. Sharmila Jayasuriya et.al. (2009) estimated equity market volatility using an asymmetric power GARCH model. The magnitude of assignment volatility for several emerging and mature markets was estimated for three sub periods.

J. XU (1999) using 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 that accounts for time varying volatility is a 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 evidence 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) investigated 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. Hojatallah Goudarzi and C. S. Ramanarayan (2010) estimated the volatility of BSE-500 stock index and its related stylized facts over 10 periods using ARCH models Their study concluded that GARCH (1,1) MODEL explains the volatility of Indian Stock Market and its stylized facts including volatility clustering, fat tail and mean reverting satisfactorily.

Wics Gunasinghe (2005) examined the integration behavior and volatility spillover transmission across the stock markets of Sri Lanka, India and Pakistan after liberalization policies were initiated in the early 1990's. He examined the ways in which two issues could relate to movement of stock prices and then investigated the impact of this on the corresponding stock markets using correlation analysis, a multivariate Co-Integration Test and Generalised Impulse Response (GIR) functions based on one factor model.

Jingle Xing (2011) empirically analysed the Chinese Stoc Market behavior by choosing the data from Shanghai Composite Index and Shenzen Stock Index. The study used ARIMA-EARCH-M (1, 1) and ARIMA-TARCH (1, 1) model to analyse the volatility of financial time series with the characteristics of clustering, asymmetry, and peak and fat tails. Giorgio Canarella and Stephen. K. Pollard (2007) used Markov Switching ARCH (SWARCH) model to document the presence of high volatility regimes in six Lain American countries consisting of Argentina, Brazil. Chile, Mexico, Peru and Venezuela. They found four high volatility episodes each associated with either a local (The Mexican Crisis of 1994, The Bazilian Crisis of 1998-1999, The Argentenian Crisis of 2001-2002) or a worldwide financial crisis (The Asian Financial Crisis of 1997). However it was revealed that the effects of each financial crisis are short lived and that between two and four months after each crisis, all market return to low volatility regimes.

Hakan Berument and Hall Kiymaz (2001) studied the Day of the Week effect on stock market volatility by using S&P 500 market index during the period of January 1973 and October 1997. The findings showed that day of the week effect are present in both volatility and return equations. They observed the highest and lowest return on Wednesday and Monday and the highest and lowest volatility on Friday and Wednesday respectively. Curto et.al. (2009) discussed the alternative conditional distributive models for the daily returns of U.S., German and Portuguese main stock market indices, considering ARMA-GARCH Models driven by Normal Student's T and stable Paretion distributed innovations. They found that GARCH model with stable Paretion innovations fits returns clearly better than the more popular Normal Distribution and slightly better than Student's T Distribution. John. J. Binder and Malthias. J. Merges (2001) examined the ability of rational economic factors to explain stock market volatility. They proposed a simple model of the economy under uncertainty, which identified four determinants of stock market volatility viz. uncertainty about price level, the riskless rate of interest, the risk premium on the equity and the ratio of expected profits to expected revenues. Their results were useful in explaining the past behavior of stock market volatility and in forecasting future volatility.

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 are 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: $Rt = c + et$

Variance Equation: $s^2_t = \omega + a_1 e^2_{t-1} + \beta_1 s^2_{t-1}$

Since s^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 (e^2_{t-1}), and the last period's forecast variance (s^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:

$$\text{Mean Equation: } R_t = c + \varepsilon_t$$

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

The left hand side of above variance equation is the logarithm of the conditional variance. This implies that the leverage effect is exponential and that the forecasts of the conditional variance are guaranteed to be non negative. In EGARCH model a is the GARCH term that measures the impact of last period's forecast variance. A positive a 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. ω 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 (ω<0). The impact is asymmetric if this coefficient is different from zero. Ideally ω 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. a+β indicates the extent to which a volatility shock is persistent over time. The stationary condition is a+β<1. Since the value of ω 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:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

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

Table 1: Summary of Statistics

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

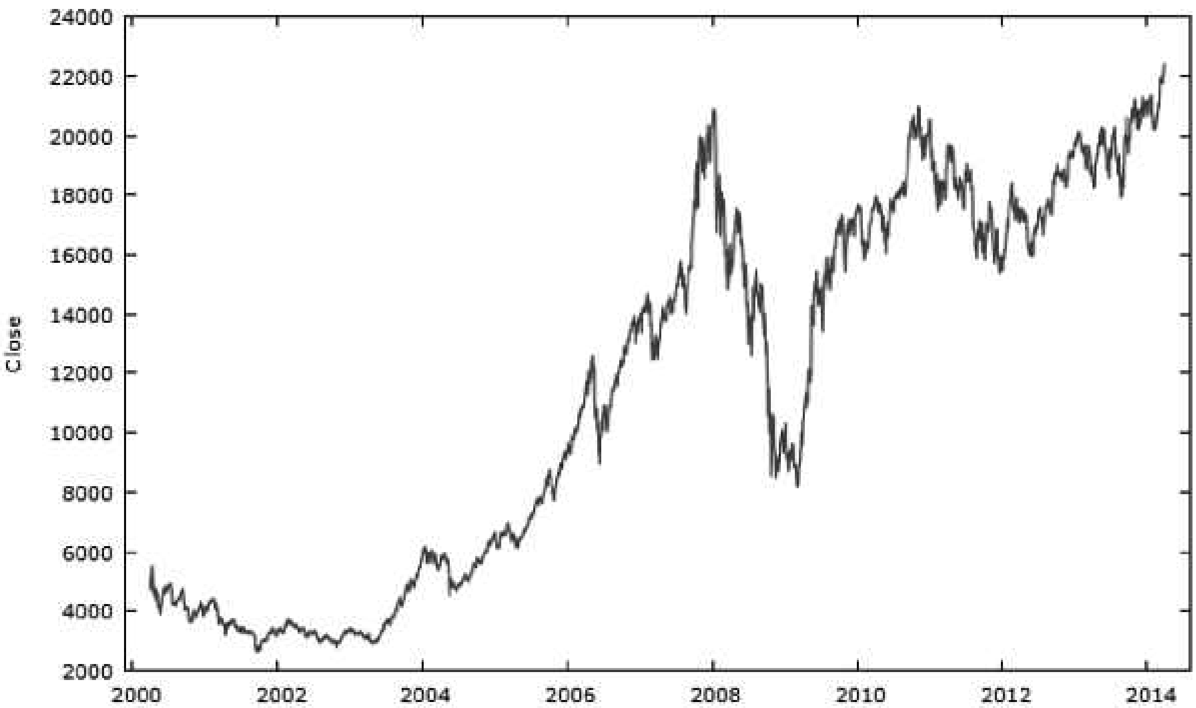

Figure 1: Time Series Plot for Close Price of BSE-SENSEX from year 2000 to year 2014

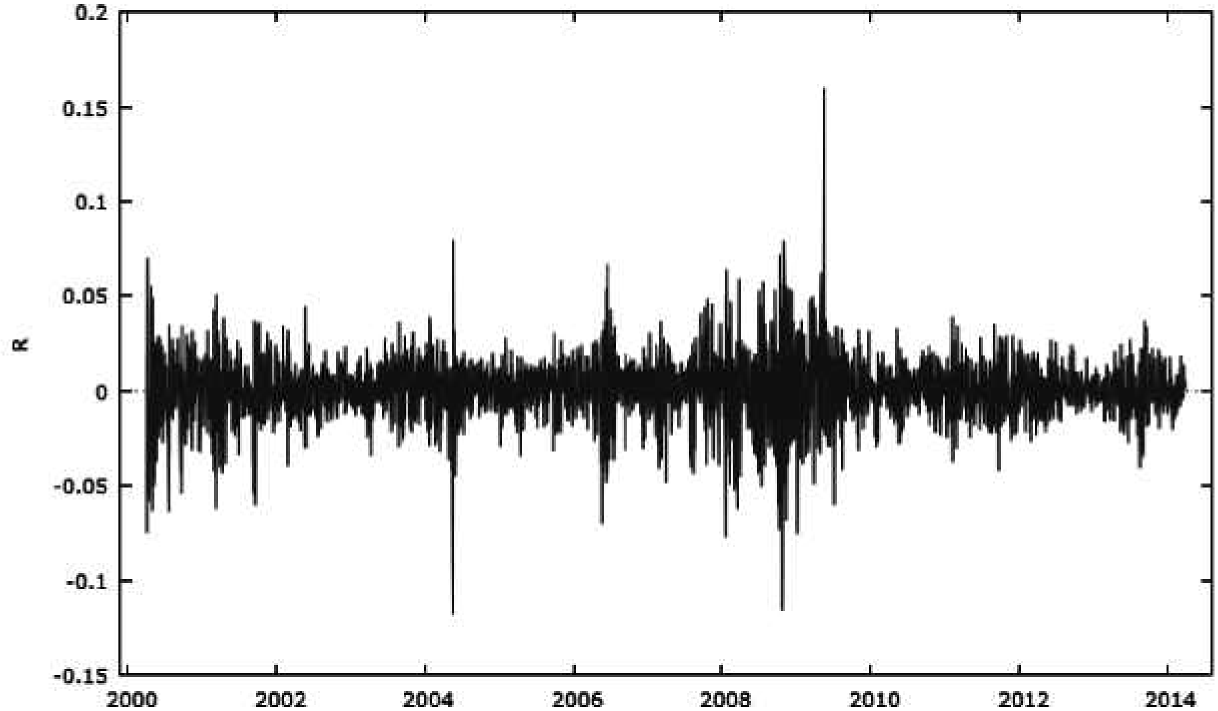

Figure 2: Time Series plot for Stock Returns for BSE SENSEX for year 2000 to year 2014

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

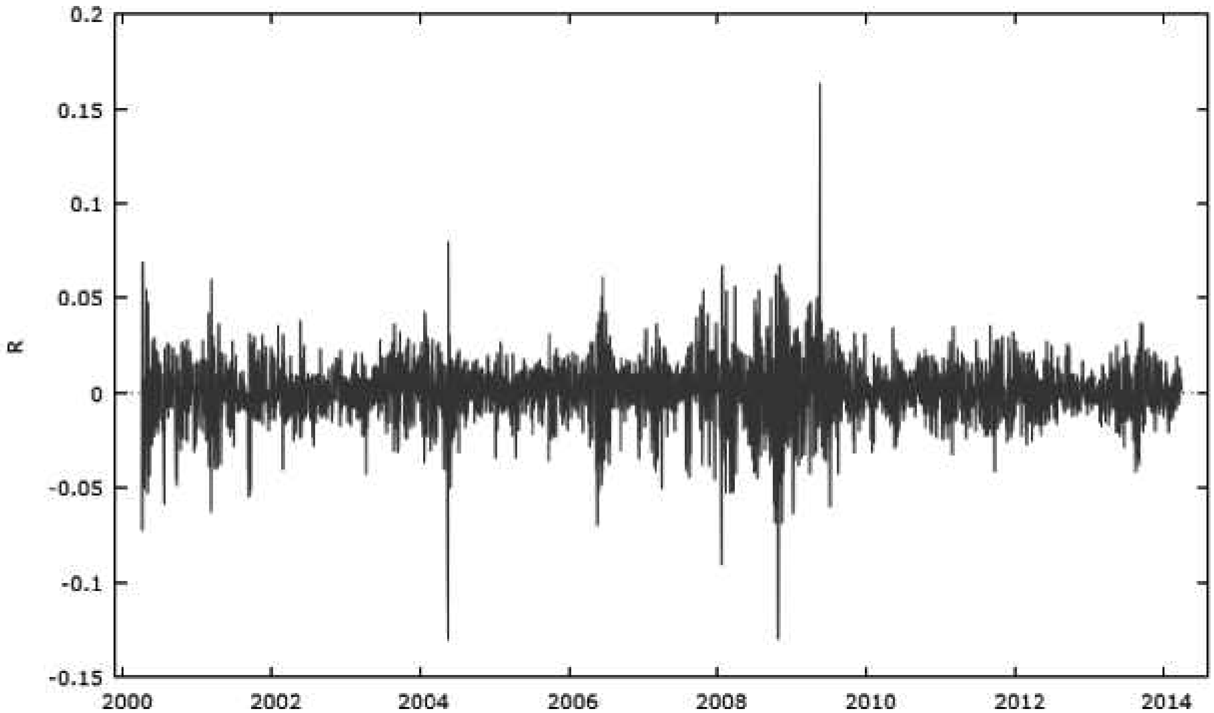

Figure 4: Time Series Plot for Stock Returns of CNX Nifty for year 2000 to year 2014

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 reveals that in case of GARCH (1, 1) Model for both BSE SENSEX and CNX Nifty the sum of ARCH and GARCH term i.e. (a+β) 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. (a+β) indicate the extent to which a volatility shock is persistent over time. Here since (a+β) for both BSE SENSEX and CNX Nifty has been greater than one i.e. 1.19 and 1.20 for BSE SENSEX and CNX Nifty respectively which points towards non stationary condition. Since ωω0, EGARCH model supports the existence of asymmetry in the stock return. A negative value of ωi.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 a = 0.1285 and a = 0.134 on volatility of BSE SENSEX and CNX Nifty respectively. Bad news has an impact of (a +ω) = 0.51 and 0.54 on the volatility of BSE SENSEX and CNX Nifty respectively. Since ω ω 0, it can be concluded that the news impact is asymmetric and there is presence of leverage effect. The Value of (a +β+ω/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 Modelling Volatility has 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 greater impact have greater impact on volatility of Indian Stock Market as compared to good news of equal magnitude. The Conditional Variance in both BSE SENSEX and CNX Nifty has been non stationary.

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