I J A B E R, Vol. 14, No. 6, (2016): 3781-3797

A STUDY ON CONDITIONAL VOLATILITY ON NIFTY EVIDENCE FROM NATIONAL STOCK EXCHANGE –INDIA

M. Tamilselvan[1] and V. Manjula[2]

Abstract: *It is impossible to forecast the future volatility of the financial assets especially equity index adopting the regular standard deviation and beta coefficient since the financial time series is featured with fatter tail, shock persistence, and clustering volatility. In order to capture the peculiar features, diverse stochastic models have been proposed. In 1982, Engle confirmed that the volatility is not constant for over a period of time using ARCH (autoregressive conditional heteroscedasticity model) and gained Nobel Prize in 2003 despite Mandelbrot (1963) and Fama (1965) initially inspected the statistical properties in time series. In extension, .Bollerslev (1986) extended the ARCH model in to GARCH (Generalized autoregressive conditional heteroscedasticity model) to overcome the deficiency of the basic model. ARCH is not efficiently modeling the shock persistence, it only models that the current variance depends on last period's squared residual. Nelson (1991) proposed EGARCH (Exponential generalized autoregressive conditional heteroscedasticity) model to measure the asymmetric presence. Glosten, Jaganathan and Runkle (1993)suggestedTGARCH (Threshold Generalized autoregressive conditional heteroscedasticity) modelto capture the leverage effect. Though enormous effort has already been put on forecasting the future volatility across the global stock markets, the consistent attempt is essential to forecast the inconsistent reaction of volatility. Besides, the literature review evidently proved that the forecasting ability of the various models is not similar due to time, data set and political instability in various markets. In this direction, the present study adopt GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models to investigate the existence of aforesaid characteristics in the Nifty Index return ,. The results of ARCH and GARCH terms of variance equation are statistically significant at 1% level which ensures the presence of persistent volatility, asymmetric and leverage effect in the Nifty Index return. The out of sample forecast confirms that the GJR model is the best forecasting model.*

Key Words: *Conditional Volatility – Shock Persistence – Leverage Effect – Asymmetric Relationship – GARCH – EGARCH - TGARCH*

INTRODUCTION

The stock market performance is considered to be one of the major indicators of the nation's economic growth. It facilitates the investors and companies to generate

[1] Faculty of Finance & Accounting, Department of Business studies, Ibri College of Technology.
[2] *Faculty of Finance & Accounting, Department of Business studies, Ibri College of Technology*
E-mail: tamilindias@yahoo.co.in

adequate return and unconditional capital. It is a platform to attract a huge amount of domestic and international capital to finance the capital intensive assets and infrastructure projects which ensure the employment opportunities and economic growth. Hence, the study on stock market performance has become a vital for academicians and practitioners. Generally the investors like individuals and institutions pick the financial assets especially equity which fetches higher return than other investments and savings. On the other hand the equity is featured with high risk. So, the investors are required to be aware of various integral risk patterns which would determine the trade-off. Therefore, the understanding and analyzing the risk component which affects the asset returns arevery significant process while formulating investment strategies. The term risk refers to variance or difference which may likely to occur in the expected future return due to various micro and macro-economic factors. The difference may be positive or negative, the later is known as risk. The total risk of the assets is estimated using simple variance or standard deviation. But in asset pricing the risk is divided in to two types such as systematic and unsystematic risks. The first one is very important which cannot be diversified and estimated using beta coefficient. These standard procedures are useful to forecast the volatility of the future returns when the volatility of the stock price movements is unconditional which is not changing in different point of times. But in reality, it is uncommon that the stock price movement is homokedastic. The price movement is assumed to be more volatile. The volatility is the conditional standard deviation of the underlying assets return and denoted by σ_t. It is assumed to follow the geometric Brownian motion derived by the Black-Scholes formula. Moles and Terry (2005) further emphasized that the price is a stochastic process with a log normal distribution. The distribution of high frequency time series data is characterized with certain features such as fatter tail, clustering volatility and leverage effect. Fatter tail refers to the excess kurtosis exists on the time series distribution which is more than standardized fourth movement of three. Clustering volatility emphasizes those large movements followed by further large movements indicating the shock persistence which is ensured with the existence of significant correlation at extended lag length in correlograms and corresponding Box-Ljung statistics. The aforesaid features of time series distribution creates the necessity for estimating and forecasting the future volatility using a wider range of stochastic econometric models. The statistical properties of a financial time series were initially inspected by Mandelbrot (1963) and Fama (1965). In 2003 Engle gained the Nobel Prize for proving that the volatility is not constant for over a period of time using ARCH (autoregressive conditional heteroscedasticity model) in 1982 for first time. Bollerslev (1986) extended the ARCH model in to GARCH (Generalized autoregressive conditional heteroscedasticity model) to overcome the deficiency of the basic model. ARCH is not efficiently modeling the shock persistence, it only models that the current variance depends on last period’s squared residual. The existence of asymmetric relationship between volatility and previous data is measured by EGARCH (Exponential generalized autoregressive conditional heteroscedasticity) model proposed by Nelson (1991). TGARCH (Threshold Generalized autoregressive conditional heteroscedasticity) model suggested by Glosten, Jaganathan and Runkle (1993) is widely used to capture the leverage effect.Black (1976) first suggested the leverage effect between price movement and volatility. Further empirical evidences are found in Nelson (1991), Gallant, Rossi and Tauchen (1992, 1993).

INDIAN MACROECONOMIC REVIEW

India is a lower-middle-income country located in South Asia. India's GDP was USD 1,870.65 billion in 2013, making it the world's 10th largest economy. India's economy is predominantly services-based. Services account for 57.03% of the GDP and employs 28.10% of the population. Manufacturing and industry accounts for 24.77% of GDP and employs 24.70% of the population. Agriculture accounts for 18.20% of GDP and employs 47.20% of the population.Government revenue in India was 20.00% of GDP in 2013, while government spending was 26.39% of GDP. The latest exchange rate, as of 04-Mar-2015, is 61.85 INR per 1 USD.India is considered by the World Bank to be "politicallyunstable.[1]The macroeconomic environment has been consistently challenging. The dawn of 21st century has witnessed a series of financial crisis such as dot.com burst (2000), twin tower attack and Enron scandal (2001) subprime crisis (2008) and global recession (2009), Euro zone crisis, Russia and Japan slowdown and China's currency devaluation. These external events are considerably affecting the growth of Indian economy. The central government and the central bank have rebuilt buffer to control and safeguard the economy from the international issues. For instance, the Indian markets were less volatile than other emerging markets in the recent financial issues like US Fed's scheme of withdrawal of asset purchase program and Ukraine crisis. The government of India has depleted the near future macro-economic instability by tapering the current account and fiscal deficit, replacement of foreign exchange reserves, adjustment of the rupee exchange rate, and more importantly, setting in motion disinflationary impulses. The annual average consumer price index inflation has been around double digit for last six years. It is a negative indication of macro financial stability which leads to high inflation, financial disintermediation, and lower financial and overall savings, current account deficit and weaker currency. In March, 2010 steps were taken to curb the inflation bit it was dulled by a series of supply side disruptions which resulted its persistence. The monetary policy increased the operational policy rate by 5.25% during March 2010 to October 2011 and continued up to April 2012. The central banks trimmed down policy rates by .75% during April 2012 and May 2013 to sustain growth. The policy moderation rooted for capital outflows and exchange rate pressures along with unsustainable current account deficit, as also renewed inflationary pressures on the back of the rupee depreciation and a vegetable price shock. As a result, in

July, 2013 the central bank was forced to constrict the monetary policy further by swelling marginal standing facility rate by 2% and cut back the liquidity availability under the liquidity adjustment facility (LAF) since July,2013. The MSF rate was lowered by 1.5% to restore the conditions and regulate the extraordinary liquidity and monetary measures in the currency market in September, 2013 by three steps. But the repo rate was hiked by .75% to restrain the inflation in three steps. The second round effect of food price pressure during June-November 2013 imposed the last round rate hike which considerably moderated the relative price shock without further rise in ex-food and fuel CPI inflation but and fuel CPI inflation at around 8 per cent for the last 20 months poses difficult challenges to monetary policy. In the given internal and external economic fragility, as predicted by the Urjit Patel Committee, the headline inflation is trending down though it continues at uncomfortable level. The GDP has witnessed less than 5% growth for last 7 successive quarters and the index of industrial production is idle for last 2 years. The potential growth has fallen with high inflation. This means that monetary policy needs to be conscious of the impact of supply-side constraints on long-run growth, recognizing that the negative output gap may be minimal at this stage.

REVIEW OF LITERATURE

Qamruzzaman(2015) examined the index return from 2004-2014 of Chittagong stock exchange (CSE) using both symmetric and asymmetric models and proved that these five models GARCH-z, EGARCH-z, IGARCH-z, GJR-GARCH-z and EGARCH-can capture the maincharacteristics of Chittagong stock exchange (CSE).Qiang Zhang (2015)found the existence strong bi-directional volatility spillover the crisis period in China and Hong Kong stock markets. Prashant Joshi (2014) forecasted daily volatility of Sensex of Bombay Stock Exchange of India from 2010 to 2014 using three different models: GARCH (1,1), EGARCH(1,1) and GJR-GARCH(1,1) and confirmed the persistence of volatility, mean reverting behavior and volatility clustering and the presence of leverage effect. Neha Saini (2014)examinedthedaily values of Sensex using autoregressive Moving Average (ARMA) and Stochastic Volatility models. The results confirmed that the volatility forecasting capabilities of both the models. Potharla Srikanth (2014)tested the Sensex return from 1997 to 2013 using GJR-GARH model and PGARCH model and revealed the presence of leverage effect in Indian stock market. Amitabh Joshi(2014)analyzed the volatility of BSE small cap index using 3 yearsdata from 2011to2013 and confirmed that ARCH and GARCH terms are significant.Mohandass (2013)investigated the fitness of volatility model in Bombay stock exchange using daily sectoral indices from 2001 to 2012. The findings concluded that the non-linear model is fit to model the volatility of the return series and recommended GARCH (1, 1) model is the best one.Naliniprava(2013) forecasted the stock market volatility of six emerging countries by using daily observations of indices over the period of January 1999 to May 2010 by using ARCH, GARCH, GARCH-M, EGARCH and TGARCH models. The study revealed that the positive relationship between stock return and risk only in Brazilian stock market. The analysis exhibits that the volatility shocks are quite persistent in all country's stock market. Further the asymmetric GARCH models find a significant evidence of asymmetry in stock returns in all six country's stock markets. This study confirmed the presence of leverage effect in the returns series. Yung-Shi Liau(2013) studied the stock index returns from seven Asian markets to test asymmetric volatility during Asian financial crisis. The empirical results showed that both volatility components have displayed an increasing sensitivity to bad news after the crisis.Ming Jing Yang (2012)explored the predictive power of the volatility index (VIX) in Taiwan market from December 2006 to March 2010. The results shown that the predictive power of the models is improved by 88% in explaining the future volatility of stock markets.Rakesh Gupta (2012) aimed to forecast the volatility of stock markets belonging to the five founder members of the Association of South-East Asian Nations, referred to as the ASEAN-5 by using Asymmetric-PARCH (APARCH) models and showed that APARCH models with t-distribution usually perform better. Praveen (2011) investigated BSE SENSEX, BSE 100, BSE 200, BSE 500, CNX NIFTY, CNX 100, CNX 200 and CNX 500 by employing ARCH/GARCH time series models to examine the volatility from 2000-14. The study concluded that extreme volatility during the crisis period has affected the volatility in the Indian financial market for a long duration. Srinivasan1(2010) forecasted the volatility of the daily sensex returns covering from 1996 to 2010. The result showed that the symmetric GARCH model perform well in forecasting conditional variance of the sensex return rather than the asymmetric GARCH models.Jibendu Kumar (2010) tested volatility of sensex and nifty return for 14 years usingdifferent methods i.e. GARCH, EGARCH, GJR- GARCH, IGARCH & ANN. The result showed that, there is no difference in the volatilities of Sensex, & Nifty estimated under the GARCH, EGARCH, GJR GARCH, IGARCH & ANN models.Amit Kumar (2009) investigatedto forecast the volatility of Nifty and Sensex using Autoregressive Conditional Heteroskedastic models (ARCH) and found that EGARCH method emerged as the best forecasting tool available, among others.Dima Alberg and Haim Shalit (2008) analyzedthe mean return and conditional variance of Tel Aviv Stock Exchange (TASE) indicesusing various GARCH models. The results showed that the asymmetric GARCH model improves overallestimation for measuring conditional variance. Floros, Christos (2008) examined the use of GARCH-type models for modelling the index of Egypt and Israel market. The study found the strong evidence that daily returns can be characterized by the above models and concluded that increased risk will not necessarily lead to a rise in the returns. Banerjee and Sarkar(2006), predicted the volatility using five-minute intervals daily return to model the volatility of National Stock Exchange, India. The result emphasized that the Indian stock market experiences volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models. Kumar. S (2006) attempted to evaluate the ability of ten different econometric volatility forecasting models to the context of Indian stock and forex markets. The findings confirmed that G.-I RCH 11. I, and EW.1 L4 methods will lead to Netter volatility forecasts in the Indian stock market and G.4RCH (5, I) will achieve the same in the forex market. Glen.R (2005) investigated the role of trading volume and improving volatility forecasts produced by ARCH and option models. The findings revealed an important switching role for trading volume between a volatility forecast that reflects relatively stale information and the option-implied forward-looking estimate.Hock Guan Ng (2004) estimated the asymmetric volatility of daily returns in Standard and Poor's 500 Composite Index and the Nikkei 225 Index daily returns. The study concluded that both the GARCH(1,1) and GJR(1,1) models show superior forecasting performance to the RiskMetrics model. In choosing between the two models, however, superiority in forecasting performance depends on the data set used.Philip (1996) studied the predictive power of GARCH model and two of its nonlinear modification to forecast weekly stock market volatility for the German stock market, Netherland, Spain, Italy and Sweden for 9 years from 1986 to 1994. The study found that the QGARCH model is the best. Glosten, L. (1993) adoptedthe modified GARCH-M model, and proved that monthly conditional volatility may not be as persistent. Positive unanticipated returns appear to result in a downward revision of the conditional volatility whereas negative unanticipated returns result in an upward revision of conditional volatility.Engle, R. and Ng, V. K. (1993), attempted to estimate news impact on volatility using daily return from Japan stock market and confirmed that the Glosten, Jagannathan and Runkle (GJR) is the best parametric model. Nelson (1991) analyzed the daily returns of CRSP value weighted index from 1962 to 1987 to propose a new ARCH model to overcome the three major drawbacks of GARCH model. The findings contribute a new class of ARCH models that does not suffer from the drawbacks of GARCH model. Akgiray (1989) presented new evidence about the time series behavior of stock price using 6,030 daily returns from Center for Research in Security Prices (CRSP) from January 1963 to December 1986. The findings observed the second order dependence of the daily stock returns which could not be modeled with linear white noise process. Therefore study concluded that the GARCH models are superior in forecasting volatility. Bollerslev (1986)introduced a new, more general class of processes, GARCH (Generalized Autoregressive Conditional Heteroskedasticallowing flexible lag structure. The extension of the ARCH process to theGARCH process bears much resemblance to the extension of the standardtime series AR process to the general ARMA process and, permits a more parsimonious description in many situations. Engle (1982) introduced a new class of stochastic process called autoregressive conditional heteroskedasticty to generalize the implausible assumptions of the traditional econometric models by estimating the means and variances of inflation in the UK. The study found significant ARCH effect and substantial volatility increase during seventies.

The extensive review of literatures relating to various international stock markets and Indian markets aptly demonstrate that the index and stock returns are subject to conditional variance with symmetric and asymmetric effect. The previous studies emphasized the adequacy of symmetric and asymmetric models and the forecasting power of various models. The market volatility is significantly being forecasted by both the models due to various factors. It is observed in the above review that the shock intensity is diverged between index return and stock return. Besides, the review depicted that the political instability is increasing the volatility in long time. Apart from this various global economic crisis, thenature of data set are considered to be key determinants of conditional variance. The vulnerable global macroeconomic factors affect the capital flow to emerging markets which led to current account deficit and high inflation eventually impacting the market volatility. The dogmatic economic scenario in last decade made Indian economy slowdown and flow of capital was depleted from advanced economy. The consequences witnessed overall negative current account balance except three years 2001, 02 and 03. The inflation inclined to almost double digit in 7 years in the study period. In 2010 the real interest rate touched negative -0.6%. In this macroeconomic fragility, forecasting the conditional volatility of Indian market could be a supplementary to the investing community. It is well appreciated that the volatility of the Indian market is being forecasted by various research scholars in different period using different data set. The review of literature revealed a mixed evidence of the models applicability in forecasting. A very few studies have been conducted in NSE – Nifty return and relatively BSE-Sensex has been tested more in number. Although, both the indices are equally important, Nifty index is consisting 50 stocks across 26 sectors. Hence, it is appropriate to testing the Nifty index. Besides the present study is motivated to test the performance of various symmetric and asymmetric models in forecasting the conditional variance persistence, asymmetrical relationship and leverage effect. The study used the new data set ranging from 2000 to 2015.McAleer (2004)provedthat the forecasting performance of models depends on the data set used.

The entire review is emphasizing the ability of forecasting characteristics of different models are not same in different market, different time and different data set.The number of equity trades on Bombay Stock Exchange (BSE)/National Stock Exchange (NSE) is ten times greater than that of Euronext or London, and of the same order of magnitude as that of NASDAQ/NYSE. The number of trades is an important indicator motivating investor interest and investor participation in equities and equity trading, and emphasizes the crucial importance of corporate governance practices in India. India scores 0.92 in the index of disclosure requirements third highest after the United States and Singapore (Naliniprava

2013). In the study period the market was actively working for 3988 days constituting 1495 days (Shri Atal Bihari Vajpayee 1100 days plus Shri Narendra Modi 395 days) in NDA rule and 2493 days in UPA rule. It had been a challenge to both the government. The economic indicators such as current account balance, export and import, inflation and interest rates had by and large been fluctuating in both NDA and UPA governments due to paradoxical global macroeconomic environment. The theoretical and conceptual frame work motivated to test the characteristics of the conditional volatility in Indian market considering the impacts of recent political instability, external forces and pressure on market and economy and new data set.

RESEARCH METHODOLOGY

As has been demonstrated earlier, since the financial time series data contains certain peculiar characteristics such as fatter tail, volatility clustering and leverage effect, it is very important to forecast the volatility persistence and asymmetrical relationship between return and volatility. Hence in the present study to forecast the conditional variance, the daily closing price of NSE – Nifty Index for the period of 16 years from 01.01.2000 to 31.12.2015 has been retrieved from National Stock Exchange official website. As the part of testing procedures, the index return is computed using the $R_t = l_n(P_t / P_{t-1})$. The calculated return series is employed as the main source of data for diagnosing the existence of stationarity, ARCH effect and clustering volatility which are essential qualities for applying GARCH models. In this direction, three sophisticated econometric models such as GARCH (1, 1), TGARCH (1,1) and EGARCH (1,1) have been adopted to capture long memory, leverage effect and asymmetrical relationship between shock and return.

GARCH (1, 1) Model

Bollerslev (1986) pioneered the following GARCH (1,1) model to overcome the weakness of the ARCH model. He argued that the conditional variance of returns is not only dependent on the squared residuals of the mean equation but also on its own past values. It is emphasized that the model is adequately capturing the clustering volatility of financial time series to control the time varying property and estimate the impact of recent and historical new on volatility. The model consists two equations such as conditional mean equation and conditional variance equation as follows.

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon^2{}_{t-1} + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2}$$

In the conditional mean equation 1 R_t denotes spot returns of Nifty Index at time "t". R_{t-1} proxy for the mean of conditional on past information. In conditional variance equation is the conditional variance of the period "t". The positive sum of ARCH (α_1) and GARCH (β_j) ensures the weak form stationary of the model if the sum is less than 1. If the coefficient sum of ARCH and GARCH is closer to 1 indicates a high degree of persistent and long memory of conditional variance.

EGARCH (1, 1) Model

The previous symmetric GARCH (1,1) model is no able to capture the yet another peculiar feature of the financial time series that is asymmetric relationship . It means that the degree of bad news impact boost the conditional volatility on stock returns is more than good news. In order to measure the asymmetricalrelationship between shocks and return Nelson (1991) derived an extended the earlier GARCH model as Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model.Drimbetas (2007) emphasized that the reaction of conditional variance is non linear on its lagged values which ensures the asymmetrical relationship.

$$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t \tag{3}$$

$$\ln(\sigma^2) = \alpha_0 + \alpha_1 \ln(\sigma^2{}_{t-1}) + \delta_1 \left|\varepsilon_{t-1} / \sigma_{t-1}\right| + \gamma^1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

Where σ_{t-1} measures the lagged conditional variance which impacts the current volatility. The informational impact of previous period volatility is measured using $\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|$. Theinformation producing leverage and asymmetric effect are detected by $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ ($\gamma^1 > 0$) and ($\gamma^1 \neq 0$) represent the leverage and asymmetrical relationship respectively. The regular parameters to be estimated are α_0, α_1, δ_1 and γ^1. The generalized error distribution is ε_t.

TGARCH (1, 1) Model

The asymmetric characteristics of conditional volatility due to positive and negative shock are very significant to measure the existence of leverage effect between nature of shock and volatility. The statistical significance of negative shock is diagnosed adopting a stochastic Threshold GARCH model (TGARCH) attaching multiplicative dummy variables. The model was jointly developed by Glosten, Jaganathan and Runkle (1993), hence it is otherwise called as GJR model. Black

(1976) argued that the scale of volatility is not same while the positive and negative shocks are equal. The negative correlation between shocks and volatility is attributes as "leverage effect" The conditional variance for the simple TGARCH model is specified as follows

$$R_t = \alpha + \beta R_{t-1} + \varepsilon_t \tag{5}$$

$$h_t = \alpha_0 + \sum \beta_i u^2{}_{t-1} + \sum \lambda_j h_{t-j} + \delta u^2{}_{t-1} d_{t-1} \tag{6}$$

It is determined that there is different impact between actual volatility and positive and negative shocks when υ_t is 1 and υ_{t-1} is negative or 0. The existence of persistence, leverage effect and asymmetrical effect is mapped out with the coefficients of estimated parameters as $\beta_j + \lambda_j + \delta/2$ (persistence), $\delta > 0$ (leverage effect) and $\delta \neq 0$ (asymmetrical relationship).Eventually the information criteria such as minimum Akaike information criteria (AIC), minimum Schwarz Information Criteria (SIC) and the maximum Loglikelihood (LL) values are used to assess the appropriate model which adequately captures the conditional volatility.

RESULTS & DISCUSSION

The calculated descriptive statistics of Nifty Index return series shown in Table-1 enumerate that the mean is equal to zero, higher standard deviation, negative skewness and the leptokurtic fashion of the return series. The results emphasize that the return series is characterized with higher fluctuation, negative asymmetric tail and fat tailed. Besides the null hypothesis of Jarque-Bera test is rejected at the 1% level to confirm the non-normality of the return series. The existence of stationarity, clustering volatility and arch effect of sample time series data are scrutinized to confirm the data validity to adopt the symmetric and asymmetric volatility forecasting models. The stationarity is proved with two different unit root tests called Augmented Dickey–Fuller test and Phillips– Perron test. The null hypothesis of both the unit root tests were rejected at 5% level since the test statistic is higher than critical value. The probability value of Obs*R-squared rejects the null hypotheis of Arch test which validates the arch effect in the return series.

The plots of the daily Nifty closing price index in the figure 1looks like a random walk. However, the visual inspection of Nifty Index return series in the figure 2 shows the presence of stationarity and the volatility clustering is depicted in the figure 3. By and large, the summary statistics of the return series seem to be best described by an unconditional leptokurtic distribution, volatility clustering and possesses significant ARCH effects. Hence, the use of GARCH-type models is deemed fit for modeling the return volatility.

Table 1
Descriptive Statisics and Diagnostic Checks on NSE-NIFTY Return

Mean		0.000403
Median		0.000974
Standard Deviation		0.015394
Skewness		-0.297082
Kurtosis		11.20961
Jarque-Bera		11255.08
Probability		0.000000
Observations		3987
Obs*R-squared		198.3138
Prob. Chi-Square(1)		0.0000
Unit Root Tests	*Test stat*	*Critical value @ 5%*
ADF – Trend&Intercept	-45.06216	-3.410933
PP – Trend & Intercept	-58.45067	-3.410933

Source: Data Analysis

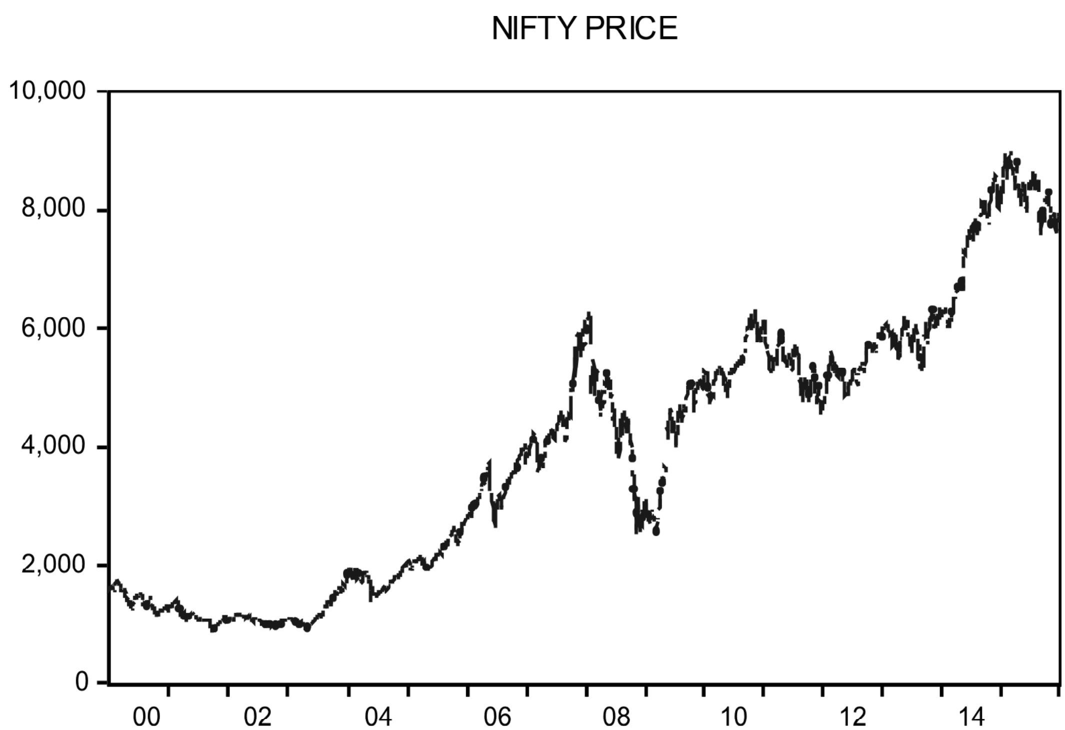

Figure 1: Daily NSE-NIFTY- Closing Price

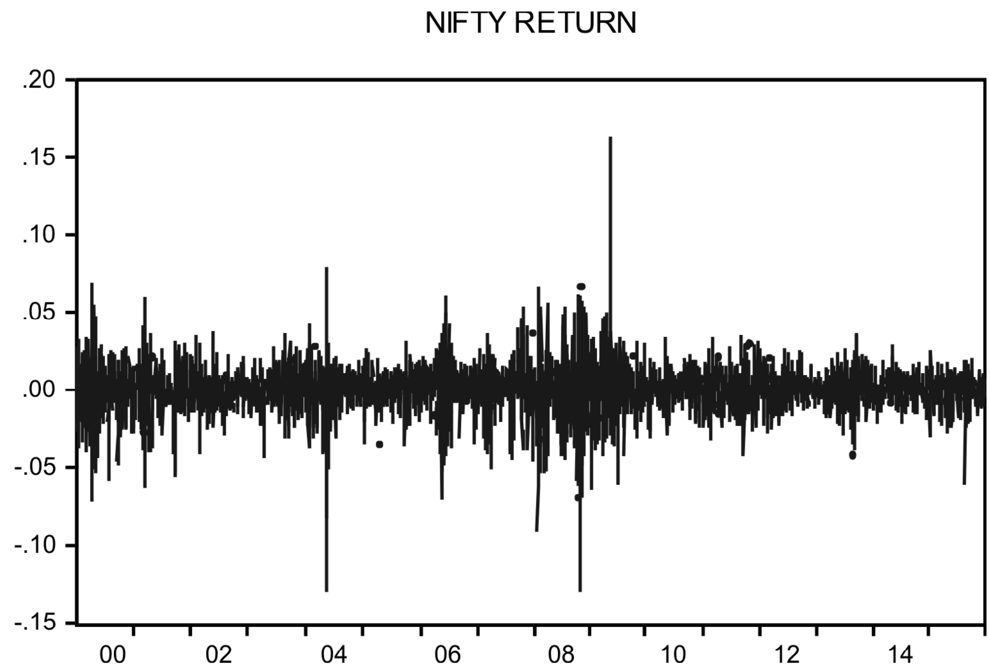

Figure 2: Daily Returns of NSE-NIFTY

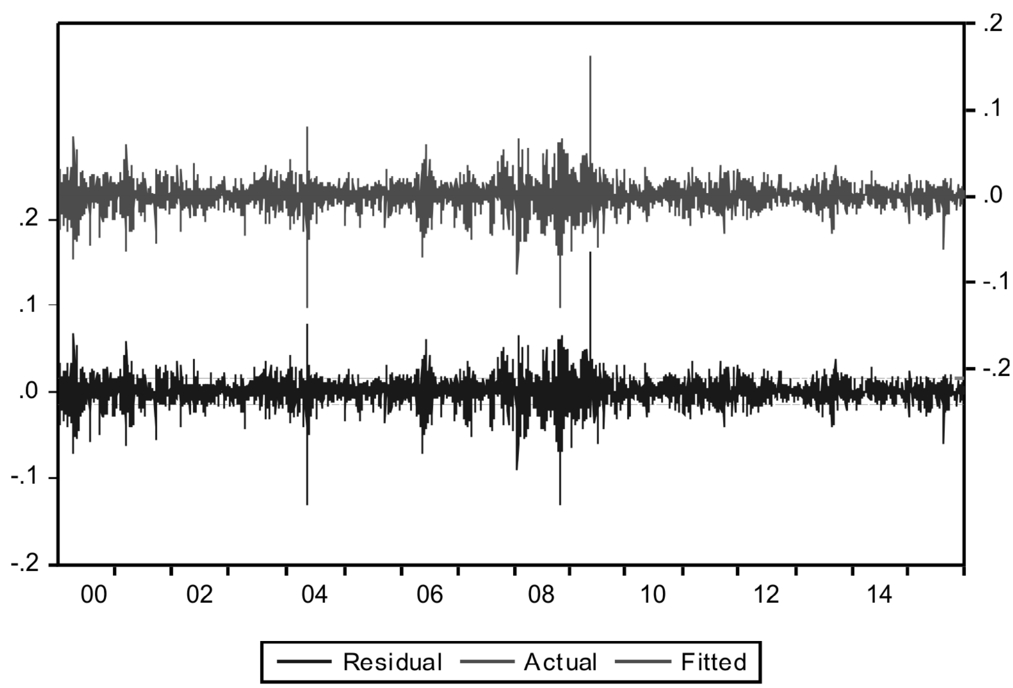

Figure 3: Clustering Volatility NSE – NIFTY Daily Returns

Table 2
Results of Estimated GRACH Family Models

GARCH (1,1) Estimates		*Co-efficient*	*z-statistics*	*p-value*
Mean Equation	α_0	0.000886	4.533670	0.0000
	α_1	0.087356	5.101123	0.0000
Variance Equation	α_0	4.89E-06	9.009963	0.0000
	α_j	0.117668	16.04713	0.0000
	β_j	0.862929	109.8725	0.0000
Akaike information criteria			-5.830713	
Schwarz information criteria			-5.822823	
log likelihood			11628.53	
TGARCH Estimates		*Co-efficient*	*z-statistics*	*p-value*
Mean Equation	*a*	0.000486	2.410643	0.0159
	b	0.099650	5.708101	0.0000
Variance Equation	α_0	5.87E-06	10.47428	0.0000
	β_j	0.044533	6.775175	0.0000
	λ_j	0.139489	11.11221	0.0000
	δ	0.859249	105.5209	0.0000
Akaike information criteria			-5.848378	
Schwarz information criteria			-5.838911	
log likelihood			11664.74	
EGARCH Estimates		*Co-efficient*	*z-statistics*	*p-value*
Mean Equation	β_0	0.000473	2.456959	0.0140
	β_1	0.104469	6.193640	0.0000
Variance Equation	α_0	-0.490423	-14.85320	0.0000
	α_1	0.227054	18.79252	0.0000
	δ_1	-0.104681	-13.38448	0.0000
	γ^1	0.963647	301.0851	0.0000
Akaike information criteria			-5.849644	
Schwarz information criteria			-5.840177	
log likelihood			11667.26	

Source: Data Analysis

The estimates of the symmetric and asymmetric forecasting models are depicted in the above table 2. The volatility is measured and observed from the calculated coefficients and the statistical significance of the coefficients. The result contains two parts such as mean equation and variance equation. The conditional heteroscedasticity is detected from variance equation using the sum of coefficients. The sum of $\alpha_1 + \beta_1$ in GARCH (1, 1) model is 0.980597is less than 1 for Nifty Index return. So, the GARCH (1,1) model is considered to be valid. The coefficient value of α_i explains that recent news is linearly related to the present volatility of the Nifty Index return. In contrast the historical volatility is measured by β_j coefficient. It is positive and higher than and implies that the recent news and past news have an impact on the volatility of Nifty Index return. The volatility dependence on its past behavior is proved the α_1 and δ_1 are statistically significant at 1% level. The characteristics asymmetric effect is found in the time series movement of Nifty Index return with the evidence of significant asymmetric coefficients. The EGARCH (1,1) result shows that γ^1 (0.963647) ensuring that the Nifty Index exhibits statistically significant asymmetric effects at one percent level. This indicates that positive shocks have greater impact on this market than the negative shocks. TGARCH (1,1) model estimated parameter of ä is (0.859249)which is greater than zero signifying the presence of leverage effect. In addition to that the estimate of β_1 (0.044533) is smaller than that of δ(0.859249),indicating that negative shocks do not have superiorinfluence on conditional volatility related to positive shocks of same extent. In the present forecasting analysis the minimum Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) ensure that the GRACH(1,1) model is the best forecasting models than the asymmetric models. On the other hand the maximum Log Likelihoodvalue emphasize that the EGARCH (1,1) is the best model for modeling the volatility of Nifty Index return. The present study recommends the asymmetric model EGARCH (1, 1).

Table 3
Forecast Performance of Estimated Models for the out of sample period

	GARCH	*EGARCH*	*TGARCH*
Root Mean Squared Error	0.010279(3)	0.010259 (2)	0.010257(1)
Mean Absolute Error	0.007620(3)	0.007586(2)	0.007585 (1)
Mean Absolute Percent Error	171.4486 (3)	165.6922 (2)	163.3032 (1)
Theil Inequality Coefficient	0.899321 (1)	0.901715 (2)	0.904742 (3)
Overall Rank	3	2	1

Source: Data Analysis
Notes: Sample forecast from 01.01.2015 to 31.12.2015. The numbers mentioned in the bracket denote rank of model. The best performing model has a rank 1.

In the Table 3, the calculated root Mean Squared Error (RMSE), the mean absolute error (MAE), the mean absolute percent error (MAPE) and the theilinequalitycoefficient (TIC) are shown. The lowest values of the errormeasurements are considered for evaluating the forecasting the overall ability .In the present study the TGARCH (1,1) model is found the best forecasting models with the overall ranking 1.Our findings areconsistent with the evidence of Engle, R. and Ng, V. K. (1993) that relatively GJR model is found superior in forecasting the conditional variance ofNifty Index returns rather than the symmetric GARCH models.

CONCLUSION

In the modern fragile macroeconomic environment which is often being determined by international economic and market information, volatility forecasting has become an integral part in formulating investment strategies. The institutional and high net worth investors seeks a consistent ideal regarding the future volatility in time varying variance. The symmetric and asymmetric behavior of the stock price movement in the future period is very significant in pricing the hybrid financial instruments.In this direction, thepresent paper attempts to modelling and forecastingthe volatility (conditional variance) of the Niftyindex returns of Indian stock market, using daily datacovering a period from 1st January 2000 to 31th December 2015. The study adopted GARCH (1,1) , EGARCH (1,1) and TGARCH (1,1) models for modeling and forecasting the time varying variance of Nifty Index return. The results of ARCH and GARCH terms of variance equation are statistically significant at 1% level which ensures the presence of persistent volatility, asymmetric and leverage effect in the Nifty Index return. The out of sample forecast confirms that the GJR model is the best forecasting model. The majority of evaluation measures in out-of-sampleforecasts emphasize that the asymmetric GARCHmodel do perform better in forecasting conditionalvariance of the Nifty Index return rather than thesymmetric GARCH models, The findings of the study areconsistent with the evidence of Engle, R. and Ng, V. K. (1993) that relatively GJR model is found superior in forecasting the conditional variance of Nifty Index returns rather than the symmetric GARCH models.

Note

1. https://www.quandl.com

References

Akgiray, V. (1989), "Conditional Heteroscedasticityin Time Series of Stock Returns. Evidence and Forecasts," Journal of Business, Vol. 62 (1),pp. 55-80.

Amit Kumar Jha (2009), Predicting the Volatility of Stock Markets and Measuring its Interaction with Macroeconomic Variables: Indian Evidence, Case Study of NIFTY and SENSEX International Journal of Sciences: Basic and Applied Research (IJSBAR) ISSN 2307-4531.

Amitabh Joshi (2014), Volatility in returns of bse small cap index using Garch (1,1), svim e-journal of applied management vol-ii, issue- i, april 2014, issn no-2321-2535.

Bollerslev (1986). Generalized Autoregressive ConditionalHeteroskedasticity Journal of Econometrics 31 (1986) 307-327. North-Holland.

Banerjee, A. and Sarkar, S. (2006), "Modeling dailyVolatility of the Indian Stock Market using intra-dayData", Working Paper Series No. 588, Indian Instituteof Management Calcutta.

Dima Alberg and Haim Shalit (2008), Estimating stock market volatility using asymmetric GARCH models, Applied Financial Economics, 2008, 18, 1201–1208.

Engle, R. F. (1982), "Autoregressive ConditionalHeteroscedasticity with Estimates of the Varianceof U.K. Inflation", Econometrica, Vol. 50 (4),pp. 987-1008.

Engle, R. and Ng, V. K. (1993), "Measuring andTesting the Impact of News on Volatility", Journal of Finance, Vol. 48 (5), pp. 1749-1778.

Floros, Christos (2008), Modelling volatility using GARCH models: evidence from Egypt and Israel.Middle Eastern Finance and Economics (2). pp. 31-41. ISSN 1450-2889.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993), "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks", Journal of Finance, Vol. 48 (5), pp. 1779-1801.

Glen. R. (2005), Volatility forecasts, trading volume, and the Arch Versus option-implied volatility trade-off, The Journal of Financial Research • Vol. XXVIII, No. 4 • Pages 519–538 • Winter 2005.

Jibendu Kumar (2010), Artificial Neural Networks – An Application To Stock Market Volatility, International Journal of Engineering Science and Technology Vol. 2(5), 2010, 1451-1460.

Hock Guan Ng (2004), Recursive modelling of symmetric and asymmetric volatility in the presence of extreme observations International Journal of Forecasting 20 (2004) 115– 129.

Ming Jing Yang (2012), The Forecasting Power of the Volatility Index in Emerging Markets:Evidence from the Taiwan Stock Market International Journal of Economics and Finance Vol. 4, No. 2; February 2012.

Mohandass (2013), Modeling volatility of bse sectoral indices international journal of marketing, financial services & management research, issn 2277- 3622 Vol.2, no. 3, march (2013).

Nelson (1991), Conditional Heteroscedasticity in Asset Returns: A New Approach, Econometrica, Vol. 59, No. 2, PP 347-370.

Naliniprava (2013), Forecasting Stock Market Volatility: Evidence From Six Emerging Markets, Journal of International Business and Economy (2013) 14(2): 69-93.

Neha Saini (2014), Forecasting Volatility in Indian Stock Market using State Space Models, Journal of Statistical and Econometric Methods, vol.3, no.1, 2014, 115-136 ISSN: 1792-6602 (print), 1792-6939 (online).

Philip (1996), Forecasting Stock Market Volatility Uisng (Non – Linear GarchModels,Jopurnal of forecasting, Vol. 15 pp. 229-235.

Praveen Kulshreshtha (2011), Volatility in the Indian Financial Market Before, During and After the Global Financial Crisis Journal of Accounting and Finance Vol. 15(3) 2015.

Potharla Srikanth (2014), Modeling Asymmetric Volatility in Indian Stock Market, Pacific Business Review International Volume 6, Issue 9, March 2014.

Prashant Joshi (2014), Forecasting Volatility of Bombay Stock Exchange International journal of current research and acdemic review - ISSN: 2347-3215 Volume 2 Number 7 (July-2014) pp. 222-230.

Prashant Joshi (2014), Forecasting Volatility of Bombay Stock Exchange, International journal of current research and academic review.ISSN – 2347-3215.

Qamruzzaman (2015), Estimating and forecasting volatility of stock indices using asymmetric GARCH models and Student-t densities: Evidence from Chittagong Stock Exchange, International Journal of Business and Finance Management Research, ISSN 2053-1842.

Qiang Zhang (2015), Global financial crisis effects on volatility spillover between Mainland China and Hong Kong stock markets Investment Management and Financial Innovations, Volume 12, Issue 1, 2015.

Rakesh Gupta (2012), Forecasting volatility of the ASEAN-5 stock markets: a nonlinear approach with non-normal errors Griffith University ISSN 1836-8123.

S. S. S. Kumar (2006), Comparative Performance of Volatility Forecasting Models in Indian Markets, Decis ion. Vol. 33, :Vo.2, July - December , 2006.

Srinivasan1 (2010), Forecasting Stock Market Volatility of Bse-30 Index Using Garch Models, Asia-Pacific Business Review Vol. VI, No. 3, July - September 2010.

Yung-Shi Liau& Chun-Fan You (2013), The transitory and permanent components of return volatility in Asian stock markets. Investment Management and Financial Innovations, Volume 10, Issue 4, 2013

https://www.quandl.com/collections/oman/oman-gdp

Reserve bank of India - Macroeconomic and Monetary Developments 2014-15.

Forecasting Volatility in the Financial Market – John Night.