Empirical Analysis of Stock Market Volatility using Implied volatility as a variable to GARCH Models

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Abstract

This study is an attempt to analyze volatility in Indian stock market. The objective of this paper is to add the informational content present in implied volatility to the GARCH models to improve its forecasting ability and to the test GARCH models in explaining the unique traits of the financial market of India, to assess its significance in capturing Indian stock market volatility and to test the relative performance of few GARCH models. This paper focuses on three types of GARCH models comprising of GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) for a time series data of Nifty for a time period of 10 years. However, we have utilized three types of GARCH models considering the symmetrical and asymmetrical aspects of the index in this paper.

Keywords: *GARCH, TGARCH, EGARCH, Implied Volatility, Nifty*

INTRODUCTION

Financial analysts all over the world are concerned with modeling accurate volatility inasset returns. Huge ups and downs in the stock prices in number of markets including developed and emerging markets worldwide are being observed. The fluctuations in the asset prices are widely believed to be the effect of changes in the economic factors like inflation, interest rates, variability in speculative market prices, unexpected events (eg. natural calamities, political unrest), and the instability of market performance. But the biggest reason for volatility in the financial market is a fall in the market performance. Empirical evidence shows that volatility normally tends to decline as the stock market rises which tends to reduce the risk. In contrast, volatility tends to escalate when the stock market falls and hence increases the risk. In order to manage such associated risk, it is important to forecast Volatility. Volatility is also a critical factor influencing the option pricing; although, it is an extremely difficult factor to forecast. Therefore, the crucial problem lies with the accurate assessment of

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volatility.

The stochastic nature of the financial market thus required development of quantitative tools to explain and analyze the behavior of stock market returns which are able to deal with such chanciness in future price fluctuations. A remarkable progress in this regard has already been made in evolving advanced econometrics tools to interpret and capture various dimensions of time series of financial data of volatilities and so as to help manage the risks associated with them. The great workforce in applied econometrics is using the Least Squares Method for estimation of Volatility. Increasingly however, econometricians are emphasizing on forecasting and analyzing the magnitude of the errors of the model.

Research in area of Volatility and its implications started with the investigation of properties of the returns in Stock. Endeavor of Mandelbrot (1963) and Fama (1965) were the first few works that investigated the statistical properties of stock returns. Engle (1982) estimated the means and variances of inflation in the U.K. and ARCH effect was found to be significant and the estimated variances increased substantially during the chaotic seventies. A uniform generalization of the Autoregressive Conditional Heteroskedastic (ARCH) mechanism introduced by Engle (1982) to allow past conditional variances in the present conditional variances equation was proposed in Bollerselv (1986). Akgiray's (1989) work presented proof on the forecasting ability of ARCH and GARCH models with regard to EWMA and the Historic Simple Average method.

The GARCH is the extension of the Autoregressive Conditional Heteroscedasticity (ARCH) model. These models are known as volatility clustering models and are largely applied to forecasting and measuring the high frequency time-varying volatility like volatility of daily stock or volatility of stock index returns. Since the foundation of these two models in the literature, they became popular and most common predominantly in financial researches as they are able to estimate the variance of a series at a particular point in time (Enders, 2004) more accurately for the financial analysts.

A lot of empirical studies used ARCH and its variants in different markets and their appropriateness in capturing the dynamic characteristics of returns of stock indexes has been demonstrated successfully. Some of the fact findings have implemented the basic/standard GARCH models across different countries along with asymmetric GARCH models are Floros (2008); Shamiri and Zaidi (2009); Elsheikh and Zakaria (2011); Islam (2013) etc. A large number of empirical researches also examined different extensions of the standard GARCH models such as the Exponential GARCH Model (EGARCH) developed by Nelson (1991), the Power GARCH Model(PGARCH) suggested by Ding, Granger and Engle (1993), the GJR-GARCH Model by Glosten, Jaganathan, and Runkle (1993), the Threshold GARCH Model (ZGARCH or TGARCH) introduced by Zakoian (1994), and so on. These are called asymmetric GARCH Models as they are proficient of modeling leverage effect and asymmetric responses.

IMPLIED VOLATILITY

Implied volatility of an option contract is that value of the volatility of the underlying instrument which, when input in an option pricing model (such as Black–Scholes) will return a theoretical value equal to the current market price of the option. Implied volatility, a forward-looking and subjective measure and differs from historical volatility because the latter is calculated from known past returns of a security.

A Model free estimation Implied Volatility, through volatility index was introduced by CBOE in 1993 based on S&P 100 options. VIX was believed to be very close to realized volatility. Indian Volatility Index called India VIX (IVIX) was introduced by the National Stock Exchange (NSE) in November 2007. The methodology of India VIX is based on VIX of

CBOE. India VIX is based on Nifty 50 index options contracts. The asymmetric relationship between the India Volatility Index (India VIX) and stock market returns demonstrates that Nifty returns are negatively related to the changes in the India VIX levels; in the case of high upward movements in the India VIX, the returns on the indices tend to move sharp downward. When the IVIX takes a U-turn, the relationship is not as significant for higher quantiles. This property of the India VIX makes it ideal as a risk management tool whereby derivative product based on the volatility index can be used for portfolio insurance against bad declines.

In this paper the focus is on the questions about volatility and the common tool is GARCH (Generalised Autoregressive Conditional Heteroscedastic) model. It focuses on three types of GARCH models comprising of GARCH (1,1), EGARCH(1,1) and TGARCH(1,1). Out of these three, GARCH is the symmetrical model and EGARCH and TGARCH are the asymmetric models. In this study, we aim to test if the symmetric and asymmetric GARCH models are capable of explaining the dynamics of returns behavior of the country's stock index for a long period of 10 years as it has not been tested before to the best of our knowledge. The main objective is to add the information content present in implied volatility as an external variable to the model. This paper is framed as follows: Introduction is followed by a thorough Review of Literature. Then Research Methodology used in the paper is described. Section after which, presents the results and Analysis. And finally, Conclusions are followed by the list of References.

REVIEW OF LITERATURE

Brailsford and Faff(1996) analyzed the forecasting models in the Australian market and concluded that still the ARCH class of models and simple regression furnish better forecasts as compared to the models previously used, although the rankings were sensitive to the error statistic used to measure the accuracy of the forecast. West and Cho (1995) found evidence in favor of the GARCH model in case of foreign exchange markets, over shorter spells and in the longer horizon no model works better.

Jacobs and Christofferson (2004) correlated number of GARCH models with different lags in option prices and returns. An objective function based for returns, while using a price for options based objective recommended a more tightfisted model.

Sollis (2005) mentioned that macroeconomic variables in 1970's had usable information content to forecast volatility and stock returns in the S&P Composite Index, but they were not usable during the 1990's, with the GARCH models. Chen and Lian(2005) highlighted the presence of asymmetry in the equity markets of five ASEAN countries, i.e, Thailand, the Philippine, Singapore, Malaysia and Indonesia and found that EGARCH and TARCH models performed better in forecasting the markets returns in Asian financial countries.

Tripathy and Garg (2013) study shows the positive relationship between risk and return in stock of Brazilian stock market, the asymmetric GARCH models find a significant indication of asymmetry in returns of all six country's stock markets, affirms the existence of leverage effect in the series of returns and indicates that negative news generates much more bounce on the volatility of the stock price in the market.

In the Indian context, Varma (1999) examined the volatility pricing of the index options by using the Black-Scholes-Merton option pricing formula and the GARCH (1, 1) model and concluded that there is severe mis-pricing in Indian Index options. He has also found the significant difference in volatility smiles for call and put options.

Kumar (2006) suggested GARCH models outperform other models in both stock and forex markets. All the measures indicate historical mean model as the worst performing model in the forex market and in the stock market. In the stock market, the forecast accuracy increases on an average of 70% by using the GARCH models when compared to other models and when observed in the forex market this improvement is to the extent of 80%. Karmakar (2006) with the experiment on TARCH(1,1) model with daily data for returns, found the presence of asymmetry in the Indian stock market. Existence of transmission effects was also found in volatilities of the stocks and Index futures of Indian market in TARCH model.

Mittal & Goyal (2012) predicted that bad news increase volatility more than good news. So the return series show 'leverage effect' and amongst asymmetric models, GARCH (1, 1) model has been found as best. MohdAminul Islam (2014) suggested in terms of performance comparison in removing autocorrelation, GARCH (1, 1) appears to be a better fit model for Malaysia and India, while TGARCH is found to have performed better for Singapore market. Indian market is more volatile or riskier for investors as compared to Singapore and Malaysia markets.

After reviewing the literature, it can be said that GARCH Models outperform any other historical model in forecasting and explaining the stock indexes of different countries. Different type of GARCH models fit differently for different time periods and countries. For ex. for Karmakar (2006), TGARCH worked well in explaining the asymmetry in Indian stock market whereas for Mittal & Goyal (2012) and MohdAminul Islam (2014), GARCH (1,1) comes out to be the best.

Christensen and Prabhala (1998) suggests that implied volatility embedded in option prices has better forecasting ability than has been previously assumed in literature.

A different type of research by Fleming et al., (1995); Giot, (2005); and Simon, (2003) focused on the informational role of options in predicting volatility. Using option prices, one can calculate the stock market's volatility implied by the option price and the pricing model. This implied volatility is a forward-looking measure of volatility for the option's lifetime. As such, implied volatility represents the market's estimate of the future volatility of the underlying asset for the lifetime of the option. Today, implied volatility indices have been constructed and published for various stock market indices around the world, have demonstrated that these implied volatility indices have significant predictive power for future stock market volatility.

Bart Frijns, Christian Tallau, and AlirezaTourani-Rad, (2008) examined implied volatility index based on the S&P/ASX 200 index options with a three-month horizon is most informative in terms of explaining stock market returns and forecasting future volatility. Prices decline more when implied volatility increases than they increase when implied volatility drops. The implied volatility index significantly improves the fit of a GJR-GARCH(1, 1) model.

Research by Potnis and Chugh, (2002)resulted in favors of the regression forGARCH (1, 1) model to forecast average realized volatility using the IVIX as feed. Dash et al (2012) used the GARCH options pricing model for options traded on the National Stock Exchange, India. They used the GARCH(1, 1) model to obtain volatility projections, and calculated option prices using these volatility projections in the Black-Scholes-Merton model. They found that the implied volatilities (for both calls and puts) were overestimated, and that call and put option prices were predominantly overvalued, and, further, that put options were more overpriced than call options. They also found that the overestimation of volatility and overvaluation of options prices increased with higher market capitalization and moderate/higher trading volume of the underlying stocks.

It is also observed that the Indian stock markets are most volatile as compared to any of the comparative markets. To better acknowledge, the Indian stock markets need some more analysis with continuous research from different perspectives to capture its volatile nature. Therefore, in this paper we focus on the volatility in Indian markets by using three different types of GARCH models for the latest data of past 10 years which comprises of the Crisis period as well.

Therefore, as per the literature GARCH models have been successful in different markets and assets under different conditions. It works well in predicting the volatility in asset prices. But in very few areas they do not give results which are up to the mark. Also, there is lot research happening with respect to Implied Volatility, which suggests that Implied Volatility captures a lot of information and is better for predicting volatility to be used for pricing derivatives. From the literature we know, GARCH Model uses Realized Volatility as a feed but from the literature we know Implied Volatility is a better measure, we do not find any literature which uses Implied Volatility with GARCH models. This Research Gap needs to be filled with the application of the above idea. To fill the above research gap we need to achieve the following objectives:

OBJECTIVES OF THE STUDY

1. To investigate the predictability of selected Volatility Models in Indian Stock Market;
2. To examine the predictability of selected Volatility Models using Implied Volatility;

To fulfill the objectives mentioned following research methodology will be used.

RESEARCH METHODOLOGY

DATA

Nifty has been taken as a proxy of Indian stock market and used its daily closing prices downloaded from online database (Bloomberg) for a 10 years period from January 2006 to December 2015. The daily index returns are expressed in the continuously compounded returns calculated as rt= log(pt)–log(pt-1) where ptand pt-1are the index prices on day t and t-1 respectively. The percentage changes in daily index prices with range of +/- 1 conditional standard deviation was plotted before proceedingfor any statistical tests, and found that the clustering effect is present in the residuals. Periods of low volatility is followed by periods of low volatility and periods of high volatility is followed by periods of high volatility. It signifies the validity for using the ARCH models.

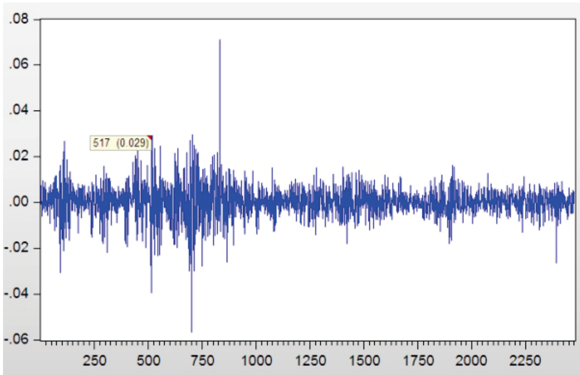
METHODOLOGY

Data has been summarized to observe the average value, skewness and kurtosis which reflect whether the data has fat tails. To check whether the financial time series (returns) are stationary and have the ARCH effect, ADF and LM test are applied respectively. A comparative analytical approach has been used to know the volatile nature of Indian Stock markets, by using Symmetrical (GARCH (1,1)), Threshold (TGARCH(1,1) and Asymmetrical (EGARCH(1,1)) models by GARCH family. Implied Volatility has been added as an informational variable to all the three GARCH models to improve the performance of GARCH models as predictors of volatility in markets. Analytical calculations have been taken care by the help of E-views.

ANALYSIS

Nifty closing prices have been taken in the Figure to show the patterns of returns of the series leading up to the terminal value. They exhibit considerable swings or volatility in the return series over the sample period. The bumping in the return plots are the graphical evidence explaining that the volatility is time varying.

Percentage changes in the log of daily index prices



In Table 1, we present some explicative statistics for return series. The results show that during the sample period, indian market observed the highest mean daily return of 7.0939%. Return series shows evidence of fat tails, since the kurtosis exceeds 3 (the normal value). Negative skewness explains that the distributions have long left tail. The Jarque-Bera (JB) test of normality clearly rejects the null hypothesis of normality. The tests explain that the distributions of the return series are non-normal.

Table 1 Summary Statistics of Index Returns Series

Mean(%)	0.018
Maximum(%)	7.0939
Minimum(%)	-5.6520
Std. Dev. (%)	6.799
Skewness	-0.020871
Kurtosis	12.12710
JarqueBera Test	8594.373
P Value	0.00

Data Stationarity Test

In order to check whether the financial time series (returns) are stationary or not, we have implemented the standard Kwiatkowski, et. al. (KPSS, 1991) test, Augmented Dickey-Fuller (ADF) test (Dickey and Fuller,1979), and Phillips- Perron (PP, 1988) test.

Table 2 Unit root test for stock returns

	Level	1st Difference	2nd Difference
ADF	-46.93812(0)	-23.04132(15)	-20.70698(26)
PP	-46.87458(5)	-498.3944(119)	-693.9949(59)
KPSS	0.055866(6)	0.029992(96)	0.016811(73)

Figures in parenthesis refer to the lag order selected based on SIC for ADF and Newey-West Bandwidth for PP and KPSS

Results of the tests are summarized in Table 2 below. These entire tests suggested that the series at level are not stationary but at first level (returns) they are stationary at 1% significance level. This ensures that we can use the time series stochastic models to test the dynamic behavior of volatility of the returns over time.

ARCH Effect

The linear structural model infers that the variance of the errors is constant over the period of time. But this assumption is not applicable for many financial data especially the stock prices or stock indices in which the errors display time-varying heteroskedasticity. Therefore, Before GARCH models are applied, it is important to ascertain the existence of ARCH effects in the residuals.

The bumping in the returns reveals the presence of volatility clustering effect in the series whereby the series exhibit some periods of low volatility and some periods of relatively high volatility. Presence of volatility clustering also implies that there is autocorrelation in the squared returns. The narrow and wide conditional standard deviation bands suggest the periods of smaller and larger daily stock price volatilities. Tight bands suggest the lower levels of risk and wide bands suggest higher levels of risk for investors holding the indices. The conditional volatility of stock price changes differs considerably over the 2006 – 2015 period with higher volatility from the beginning of 2007 till mid-2009 followed by a relatively smaller volatility up to the terminal period as shown by the tight standard deviation bands.

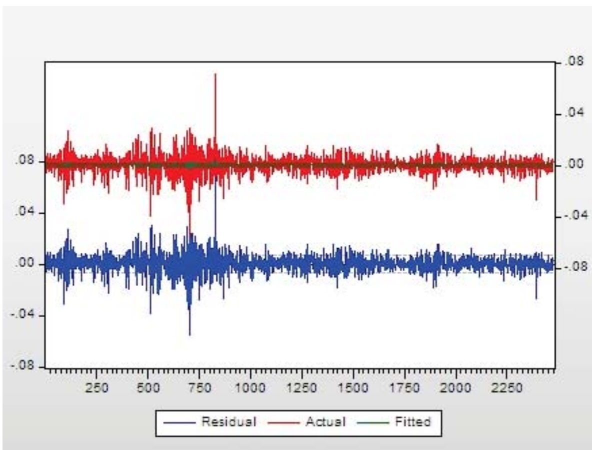


Table 3 ARCH LM Test

Statistic	40.86384
Prob chi-square	0.0000
Fstatistic	41.51655
Prob(f statistic)	0.0000

If the value of the LM version of test statistic is greater than the critical value from the χ 2 (q) distribution, or lagged term coefficients statistically significant, there is no ARCH effect in equation then the null hypothesis is rejected (1). We carried out the test for a lag order of q=3. The test results are presented in Table 3.

Applying GARCH

Chosen GARCH models are estimated as follows

GARCH(1, 1):

$$\sigma_t^2 = 0.000000518 + 0.093316\varepsilon_{t-1}^2 + 0.897219\sigma_{t-1}^2$$

Here we see that the value of ±+2 is very close to one (0.093316+0.897219) that signifies that the volatility has an high conditional effect in the selected time period of the nifty. Yesterday's volatility and yesterday's innovation explains most of today's volatility.

TGARCH(1,1):

$$\tilde{A}_t = 0.000000661+0.040892|\mu_{t-1}| +0.118664| \mu_{t-1}| I(\mu_{t-1}<0)+0.889309\tilde{A}_{t-1}$$

As expected we get a positive value for 3i which signifies bad news have larger impacts on the volatility of the returns. Therefore, as we observe that the threshold values are different from zero, we can predict that only large shocks attract investors' attention in the Indian Stock market.

EGARCH (1,1):

$$\log(s_t^2) = -\ 0.395820 + 0.201402-|z_{t-1}| - E(|z_{t-1}|)- + 0.088897z_{t-1} + 0.002895\log(s_{t-1}^2)$$

Here the exponential nature of the conditional variance assumes that the external unexpected news will exert stronger influence. A non-zero value of γ here indicates the existence of asymmetrical effect in the returns with volatility and a non- negative value indicates there is no presence of leverage effect.

Now to improve the estimated volatility as a predictor we add implied volatility as an additional variable to the selected models and get the following results:

GARCH (1, 1):

$$\sigma_t^2 = 0.008635 + 0.039687\varepsilon_{t-1}^2 + 0.950335\sigma_{t-1}^2 + 0.014177iv_{t-1}$$

By adding implied volatility to GARCH (1,1) we observe that the value of the estimates has become even closer to one (0.039687+0.950335+0.014177), which signifies the importance of the informational content present in implied volatility in predicting volatility. Also, it can be observed that by adding implied volatility as an additional variable to the model the estimates of yesterday's expected volatility has also improved.

$$\text{TGARCH (1,1)}: \sigma_t^2 = 0.013538 + 0.023711\,\mu_{t-1}| + 0.060861|\mu_{t-1}|I(\mu_{t-1}<0) + 0.935923\tilde{A}_{t-1} + 0.012435iv_{t-1}$$

Here also it can be observed that the positive value for γi gives us the results as expected according to the literature's rules. Also, the value of the estimates improves. So, by adding the information content present in implied the model fits better for the Indian stock market.

$$\text{EGARCH (1,1):} \quad \log(\sigma_t^2) = -0.068438 + 0.086050(|z_{t-1}| - E(|z_{t-1}|)) + 0.041698 z_{t-1} + 0.991412 \log(\sigma_{t-1}^2) + 0.012873 iv_{t-1}$$

Here also the non-zero value of γ and non-negative estimates show existence of asymmetrical effect in the returns andno presence of leverage effect respectively. But a lot of improvement can be seen in the estimates.

CONCLUSION

In this paper, we have estimated three of the GARCH family models: GARCH (1, 1), EGARCH (1,1) and the TGARCH (1, 1). The objectives of this paper are to test these models in explaining the unique traits of the financial market of India and to assess their significance and to improve the predictability of the selected models by adding more information present in implied volatility. The key results of this study are as follows: Firstly, GARCH models can be used for a longer period of 10 years as well. ARCH Effect has been tested for three models and is found to be positive. It signifies the presence of clustering effect in the Indian stock markets. Secondly, Symmetric and asymmetric models work well for the Indian markets. All three models are found to be sufficiently capable of capturing the dynamics of the Indian financial markets particularly with respect to volatility clustering, the leptokurtic characteristic of the distribution of the daily return series and the asymmetric effects. Therefore, we can say that GARCH family models work well in Indian Context as they fulfill the given conditions of the model. Also, Indian stock market reflects importance of thresholds and shows that the investors react to shocks in the market.

Thirdly, when information content of the implied volatility was added as a variable to the model, it is seen that the model improves. Not only the value of estimate of implied volatility adds to the model but the value of yesterday's estimated volatility in the models improves drastically. It is very near to today's estimated volatility as it improved through the process of modelling the volatility. Therefore, the objective of the research is fulfilled and gives significant results in favor of the thought of using information content present in implied variable as an additional variable to the selected volatility models. The results of the study can be beneficial for traders and investors in making investment decisions by applying these models and analyzing the best results for Volatility. However, we have utilized only three types of GARCH models in this paper. There are a number of variations of GARCH type-models that are present such as- Power GARCH, Component GARCH to name a few that can be considered well worth for further study in assessing the characteristics of the markets by extent of these models' abilities.

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