# Predicting Stock Market Volatility using Implied Skew

**Himani Arya**
**Research Scholar, School of Management, Gautam Buddha University**
Gautam Buddh Nagar, UP (India) - 201308

**Dr. Dinesh K Sharma**
**Assistant Professor, School of Management, Gautam Buddha University**
Greater Noida, Gautam Buddh Nagar, UP (India) - 201308

**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 Skew 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. We have utilized three types of GARCH models considering the symmetrical and asymmetrical aspects of the index in this paper. This paper focuses on three GARCH models GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) for a time series data of Nifty for a time period of 10 years.

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

## INTRODUCTION

Analysts in the field of finance are concerned with modeling accurate volatility in asset returns. Fluctuations in asset prices in markets including developed and emerging are under huge observation and are 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 as per the research the biggest reason for volatility in the financial market is a fall in the market performance. Empirical researches have given evidences for volatility stabilization as the stock market rises which is just because of the reduction in risk. Therefore obviously in contrast, volatility tends to increase when the stock market falls due to the increases in the risk. With respect to this uncertainty, it has become important to forecast Volatility in order to manage such associated risk. Volatility also is a crucial factor in the option pricing; though, it is extremely difficult to forecast it. Therefore, the critical role lies with the best assessment of 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. Research in area of Volatility and its implications started with the investigation of properties of the returns in Stock. ARCH effect was found to be significant and the calculated variances increased enough during the chaotic seventies. 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 Skew**

When we talk about Implied Volatility and its Performance or say Information Content associated with it, we want to apply the predictability in option price for Risk Management. And it is known empirically to improve the predictability of Implied Volatility we add information present in its Skew. Volatility skew is the difference between the implied volatilities of out-of-the-money put and out-the-money calls option contracts. Volatility skew is affected by the view and the demand supply of the option contracts based on information on whether fund managers are going for call or put options. The volatility skew basically comprises of a minimum of three types of information: the possibility of a jump in price, the degree of expected price jump, and the premium that investors can afford to compensate the risk of a jump and also the risk of a large jump.

The information embedded in volatility skews is related to future earnings shocks, in the sense that firms with the steepest volatility skews have the worst earnings surprises. The steepest volatility skews are those experiencing the worst earnings shocks in subsequent months, suggesting that the information embedded in the shape of the volatility smirk is related to firm fundamentals. Finally, in order to examine the speed at which markets adjust to public information, traders develop trading strategies based on past volatility skews and examine risk-adjusted returns of these trading strategies over different holding periods.

Volatility skew has significant predictive power for future cross-sectional equity returns. Informed traders might choose to trade in different assets and markets to benefit from their informational advantage.

This paper focuses on the questions about volatility and the common tool is GARCH (Generalised Autoregressive Conditional Heteroscedastic) model. 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 skew 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

Endeavor of Mandelbrot (1963) and Fama (1965) were the first few works that investigated the statistical properties of stock returns. Also, Brailsford and Faff (1996) analyzed the forecasting models in the Australian market and concluded ARCH class of models and simple regression furnish better forecasts as compared to the models previously used. 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.

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.

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. Mohd Aminul 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.

Adding to the research there was a new concept of Skew which gave us the directions as well.

Bates (1991) argues that the set of index call and put option prices across all exercise prices gives a direct indication of market participants’ aggregate subjective distribution of future price realizations. Therefore, OTM puts become unusually expensive (compared to ATM calls), and volatility smirks become especially prominent before big negative jumps in price levels, for example, during the year preceding the 1987 stock market crash.

Pan (2002) incorporates both a jump risk premium and a volatility risk premium and shows that investors’ aversion toward negative jumps is the driving force for the volatility smirks. For OTM put options, the jump risk premium component represents 80% of total risk premium, while the premium is only 30% for OTM calls. Put differently, investors tend to choose OTM puts to express their worries concerning possible future negative jumps. Consequently, OTM puts become more expensive before large negative jumps.

Xing, Zhang and Zhao document the prevalent existence of volatility smirks in individual stock options. From 1996 to 2005, more than 90% of the observations for all firms with listed options exhibit positive volatility smirks, with a median difference between OTM put and ATM call-implied volatilities being roughly 5%. Also, they demonstrated that the implied volatility smirks exhibit economically and statistically significant predictability for future stock returns.

Bruno et al. (2009) said conditioning on skewness increases the predictive power of the volatility spread and that coefficient estimates accord with theory. DeMiguel, et al.(2011) suggested option-implied information can be used to improve portfolio selection by using Option-implied skewness. Peter Carra, Liuren Wu suggested that skew models strongly outperform traditional jump-diffusion stochastic volatility models, both in sample and out of sample.

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 Mohd Aminul Islam (2014), GARCH (1,1) comes out to be the best.

It is also observed that the Indian stock markets are most volatile as compared to any of the comparative markets. Also, as per the literature, Implied Volatility captures a lot of information for the future move which is going to happen in the market and Implied Volatility skew gives us the idea for direction of the volatility move and increases the predictive power of volatility used for pricing derivatives. Therefore, in this paper we focus on the volatility in Indian markets by using three different types of GARCH models and add Volatility Skew as an informational variable to enhance the predictive power of the existing models for the latest data of past 10 years which comprises of the Crisis period as well. We do not find any literature which uses Implied Volatility Skew 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 examine the presence of ARCH effect in the Indian Stock Market;
2. To examine the performance of selected Volatility Models using Implied Volatility Skew;

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

## RESEARCH METHODOLOGY

**Data**

Daily closing prices for Nifty are downloaded from online database (Bloomberg) for a 10 years period from May 2007 to May 2017. The daily index returns are expressed in the continuously compounded returns calculated as $r_t = \log(p_t) - \log(p_{t-1})$ where $p_t$ and $p_{t-1}$ are the index prices on day $t$ and $t-1$ respectively. Implied Volatility data has been taken for 30 days option contract. Skew has been calculated by generalizing 90% and 110% moneyness of the contract.

**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. The percentage changes in daily index prices with range of +/- 1 conditional standard deviation are plotted before proceeding for any statistical tests, and found that the clustering effect is present in the residuals. Implied Volatility Skew 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. A 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. Analytical analysis is done with the help of E-views.

## ANALYSIS

Explicative statistics for return series given in Table1 show that during the 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 (%) | Maximum (%) | Minimum (%) | Std. Dev. (%) | Skewness | Kurtosis | Jarque Bera Test | P Value |
|---|---|---|---|---|---|---|---|
| 0.018 | 7.0939 | -5.652 | 6.799 | -0.0209 | 12.1271 | 8594.37 | 0 |

**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**

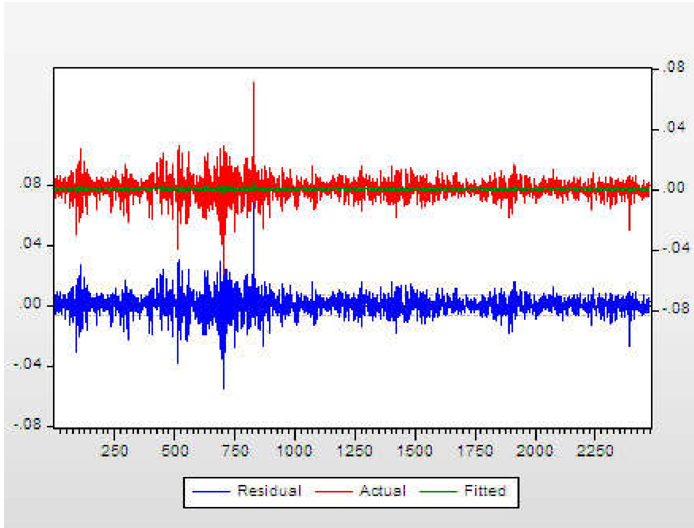
| | Level | 1st Difference | 2nd Difference |
|---|---|---|---|
| ADF | -46.93812(0) | -23.04132(15) | -20.70698(26) |
| PP | -46.87458(5) | -498.3944(119) | -693.9949(59) |
| KPSS | 0.055866(6) | 0.029992(96) | 0.016811(73) |

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 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.




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

| **Table 3 ARCH LM Test** | | | |
|---|---|---|---|
| Statistic | Prob chi-square | Fstatistic | Prob(f statistic) |
| 40.8638 | 0 | 41.5166 | 0 |

**Applying GARCH with Implied Volatility Skew**

Chosen GARCH models estimated for 30 day contract are as follows:

GARCH (1,1): $\sigma_t^2 = 0.00000113 + 0.072858\varepsilon_{t-1}^2 + 0.915134\sigma_{t-1}^2 + 0.00000211 ivs_{t-1}$

Here we see that the value of $\alpha_s + \beta_s$ is very close to one ($0.072858 + 0.915134 + 0.00000211$) that signifies that the volatility has a high conditional effect in the selected time period of the nifty. Yesterday's volatility and yesterday's innovation explains most of today's volatility. Also, it can be observed that by adding implied volatility skew as an additional variable to the model, the estimates of expected volatility has improved.

TGARCH (1,1): $\sigma_t = 0.00000126 + 0.026662|\varepsilon_{t-1}| + 0.105695|\varepsilon_{t-1}|I(\varepsilon_{t-1}<0) + 0.908187\sigma_{t-1} + 0.0000022 ivs_{t-1}$

As expected we get a positive value for $\gamma_i$ which signifies bad news have larger impacts on the volatility of the returns. As we observe that the threshold values are different from zero, we can predict that only large shocks attract investors' attention and by adding the information content present in implied the model fits better for the Indian stock market.

EGARCH (1,1):

$$\log(\sigma_t^2) = 0.307133 + 0.148231\left(|z_{t-1}| - E(|z_{t-1}|)\right) + 0.081373 z_{t-1} + 0.977916 \log(\sigma_{t-1}^2) + 0.117847 ivs_{t-1}$$

Here the exponential nature of the conditional variance assumes that the external unexpected news will exert stronger influence. A non-zero value of $\gamma$ 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. But a lot of improvement can be seen in the estimates by adding implied volatility skew as another variable.

**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 and assess their significance and to improve the predictability of the selected models by adding more information present in implied volatility skew. 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 existing. 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 presented in implied volatility skew is added as a variable to the model, it is seen that the model improves. Not only the value of estimate of implied volatility skew 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 modeling 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, there are a number of variations of GARCH type-models 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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