Estimating and Forecasting Volatility Using ARIMA Model : A Study on NSE, India

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Abstract

Volatility has been used as an indirect means for predicting risk accompanied with an asset. Volatility explains the variations in returns. Forecasting volatility has been a stimulating problem in the financial systems. This study examined the different volatility estimators and determined the most efficient volatility estimator. The study described the accuracy of the forecasting technique with respect to various volatility estimators. The methodology of volatility estimation included Close, Garman - Klass, Parkinson, Roger - Satchell, and Yang - Zhang methods and forecasting was done through the ARIMA technique. The study evaluated the efficiency and bias of various volatility estimators. The comparative analyses based on various error measuring parameters like ME, RMSE, MAE, MPE, MAPE, MASE, and ACF1 gave the accuracy of forecasting with the best volatility estimator. Out of five volatility estimators analyzed over a period of 10 years and after critically examining them for forecasting volatility, the research obtained Parkinson estimator as the most efficient volatility estimator. Based on various error measuring parameters, Parkinson estimator was found to be the most accurate estimator based on RMSE, MPE, and MASE in forecasting through the ARIMA technique. The study suggested that the forecasted values were accurate based on the values of MAE and RMSE. This research was conducted in order to meet the demand of knowing the most efficient volatility estimator for forecasting volatility with high accuracy by traders, option practitioners, and various players of the stock market.

Keywords : NSE, volatility, forecasting, CNX Nifty index, volatility estimators, ARIMA

JEL Classification : C22, C53, C58, G17

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Financial markets around the globe have different participants ranging from naive investors to fund managers, FIIs, FPIs, DIIs, and policy makers. The fundamental purpose of participants is to predict the market or to forecast the ups and downs in the movement of prices so that they can make a calculated move to gain positive returns. In predicting the prices of stocks, indices, and commodities, volatility and its measures have played an important role. Volatility helps in knowing present and future directions by using historical data and the extent to which the stock market will move. Volatility describes the deviation in the returns of the share prices, indices, or commodities. Volatility can be calculated as the standard deviation of log returns.

Different methods of estimating historical volatility have been examined. In addition to close-to-close method, advanced volatility estimators like Garman - Klass, Rogers and Satchell, Parkinson, and Yang - Zhang have been examined. Among different time series forecasting models, the ability to forecast accurate volatility defines the

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success or failure of different volatility measuring models. It is very important to examine the accuracy of time-varying models for managing and measuring risk, derivative asset pricing, trading strategies, and to know the dynamics of time series data. Various time-varying volatility models are used for forecasting future volatility. Various statistical methods are widely used for estimating volatility, however, the autoregressive time series models like ARIMA[1] (autoregressive integrated moving average) have outperformed statistical methods in various forecasting analysis.

Since different volatility estimators have different efficiency in contrast to close-to-close method, so they are expected to have different accuracy in forecasting. Based on error measuring parameters, that is, mean error, mean absolute error, mean absolute percentage error, mean percentage error, mean absolute scaled error, root mean absolute error, and autocorrelation of errors at lag 1, the accuracy of the estimators is compared.

The study considers the time series data of CNX Nifty Index from the National Stock Exchange, India. National Stock Exchange has a total market capitalization of more than US$1.41 trillion, which makes it the 12th largest stock exchange in the world. Around 22 sectors of the Indian economy are covered by the CNX Nifty Index, and thus, offers the portfolio managers (or investment managers), an exposure to the Indian stock market in one collection. CNX Nifty Index is the most actively traded contract as surveyed by WFE, IOMA, and FIA.

Literature Review

From the last two decades, enormous research has been conducted in the field of volatility in context to predicting and forecasting. Many researchers applied autoregressive ARIMA model for forecasting volatility. ARIMA models have been used for forecasting the gold price, the oil and natural gas prices in commodities market, but not much has been done in context of volatility estimation or forecasting for the Indian stock market.

The volatility models for estimation and forecasting in context to stocks and derivative market have been improved over the decades. Some of the research studies in volatility estimation include contributions from Parkinson in 1980, Garman and Klass in 1980, Rogers and Satchell in 1991, and Yang and Zhang in 2000 (Bennett & Gil, 2012). In the various experiments, it was shown that Parkinson volatility estimator was five times more efficient than the classical close-to-close estimator. While Garman - Klass volatility estimator and Roger - Satchell estimator showed 7.4 times more accuracy in comparison to close-to-close method, Yang - Zhang estimator was 14 times more accurate in comparison to the close-to-close estimator. Among many research studies related to volatility prediction in context to the National Stock Exchange, few have used the volatility estimators to check their suitability for forecasting. Tripathy and Gil - Alana (2010) studied data of three years and concluded that Parkinson's performance was lowest among all the volatility estimators on the basis of low adjusted R^2.

Rajan (2011) described in his study various time series models for modelling volatility for SENSEX. This study suggested that among various GARCH models, TGARCH had the capability of capturing the irregular behaviour of stock market and estimating volatility for SENSEX.

As'ad (2012) studied four ARIMA models for forecasting daily peak electricity demand. The study revealed that forecasting for two to seven days ahead, the ARIMA model using three months past data is the best model. Using error parameters, RMSE and MAPE, it was also shown in the study that 6 months of past data could best predict one day ahead using the ARIMA model. Devi, Sundar, and Alli (2013) studied time series analysis in context to five stocks from Nifty Midcap 50 and based on the best-fitted model, forecasted the stock prices. Rotela Jr., Salomon, and Pamplona (2014) evaluated the performance of ARIMA model in comparison to other

[1]ARIMA (auto regressive integrated moving average) model is defined as generalization of ARMA (auto regressive moving average) model in econometrics and particularly in time series analysis. ARIMA model is fitted to time series data to forecast the future points in the data.

smoothing models for forecasting the Bovespa Stock Index. A study was conducted in estimation and forecasting of volatility using ARIMA technique with time - series data from the S&P 500 Index. Ariyo, Adewumi, and Ayo (2014) demonstrated different ARIMA models' building process for price prediction of stocks for a short term duration. Researchers found that the ARIMA model had robust prospective for stock prediction in short term as compared to other prevailing prediction techniques. Mondal, Shit, and Goswami (2014) examined the effectiveness of ARIMA model while studying the 56 Indian stocks of different sectors of the economy. Among all the various sectors, the study analyzed the predicting accuracy of the stock prices, and it was found to be 85%, which gave a view that ARIMA forecasts with good accuracy.

Kumar and Patil (2015) examined the different volatility estimators and based on different error measuring parameters, the study found that the Garman - Klass estimator with ARIMA technique forecasted volatility with high accuracy. Kumar and Anand (2015) used Box - Jenkin's ARIMA model to forecast the sugarcane production in India upto 5 years. The study revealed the growth in production for the year 2013 and then a sharp dip in 2014 followed by growth of approximately 3% in successive years from 2015 to 2017.

Mattack and Saha (2016) studied the effect of volatility due to the introduction of derivatives on the underlying asset with the help of ARMA - GARCH models. The study further found that the volatility decreased over the period due to the listing of derivatives in the Indian stock market. Singh, Devi, and Roy (2016) analyzed the time - series data for index of industrial production of India and found that trend and seasonal effects were present in the IIP. Forecasting of IIP of India using ARIMA model depicted a decline in rainy season and then showed further considerable increase after August 2016. Guha and Bandyopadhyay (2016) forecasted the gold prices for Multi Commodity Exchange of India Ltd. (MCX) using the ARIMA model. One out of six different model parameters was chosen as the best model (ARIMA (1, 1, 1)) because it satisfied all the benchmarks of fit statistics. Murthy, Anupama, and Deeppa (2012) addressed the applicability of ARIMA (0, 1, 0) as a forecasting tool and studied the performance of short - term forecasted values and long term forecasted values of gold price. ARIMA (0, 1, 0) with log transformation was found out to be valid and a comparatively better model than other ARIMA models.

Kumar and Khanna (2018) examined the volatility behaviour with ARCH, GARCH, and GARCH - BEKK model and analyzed volatility spillover in stock markets among India, Japan, China, and Hong Kong. The study resulted in claiming the Indian financial market as a stable market among other stock markets studied and that the previous shocks and news impacted the current volatility.

The present study examines the various literatures on volatility estimation, volatility forecasting, and ARIMA models. This study, while addressing the issue of accuracy of the ARIMA model in forecasting volatility, and the efficiency of various volatility estimators with respect to the Indian stock market, made an effort to estimate and predict the best estimator based on accuracy from ARIMA technique for forecasting in context to CNX Nifty Index.

This study contributes to the literature firstly by bringing forth the accuracy results of various volatility estimation techniques, which have not been analyzed for the Indian stock market. Secondly, ARIMA and GARCH models were studied for volatility clustering, calendar effect, volatility shocks, casualties, etc. but not the accuracy of the forecasted values. This research studied the accuracy of forecasted values with different volatility estimators, which makes it unique in context to the Indian stock market.

Research Objectives

(1) To determine the efficient volatility measures based on empirical performance of different volatility estimators with respect to close-to-close method.

(2) To examine the accuracy of different volatility estimators using the ARIMA model.

Data and Methodology

The stock market data for CNX Nifty Index from January 1, 2007 till December 30, 2016 for the period of 10 years was extracted from the National Stock Exchange, India in Quandl database. The data was imported from Quandl to RStudio (Integrated Development Environment for R). The CNX Nifty Index, also known as Nifty 50, is an index comprising of 50 companies listed on NSE as well as BSE (Bombay Stock Exchange). This study uses the end of day - trading data for volatility calculations. The data were arranged in increasing order of the dates. Dataset includes high, low, close, open price for trading days (approx. 21 days in a month) in 10 years, which included 2474 observations.

The performance criteria for estimating the best volatility estimators are bias and efficiency. Four performance criteria for bias and efficiency are as follows :

(i) Bias $= E(V_i - V_c)$

(ii) Relative Bias $= E[(V_i - V_c)/ V_c]$

(iii) Mean Square Error $= E[(V_i - V_c)^2]$

(iv) Mean Absolute Difference $= E[\text{Abs}(V_i - V_c)]$

where,

V_i = Volatility estimated by the estimator.

V_c = Volatility estimated by close-to-close method.

Bias measures bias and relative bias measures the magnitude of the bias. Mean square error (MSE) and mean absolute difference (MAD) both measure efficiency of the estimator. Difference between MSE and MAD is that MAD measures efficiency, which is not affected by the negative extreme value in the data set.

Historical or realized volatility estimation efficiency measures the variance of corresponding estimator. It estimates maximum performance against the idealized distribution or true value. In this study, close-to-close estimation had been taken as idealized distribution for computing efficiency of different volatility estimators. Efficiency can be calculated as follows :

$$\textit{Efficiency}, \sigma_{(x)} = \frac{\sigma^2_x}{\sigma^2_{cc}}$$

where,

σ^2_x = volatility estimated by estimator,

σ^2_{cc} = volatility estimated by close - to - close method.

Different volatility estimation methods require daily financial data for the trading price of Nifty 50 which is in the form of OHLC (open - high - low - close). The following notations have been used for different prices :

O_i = morning opening price,

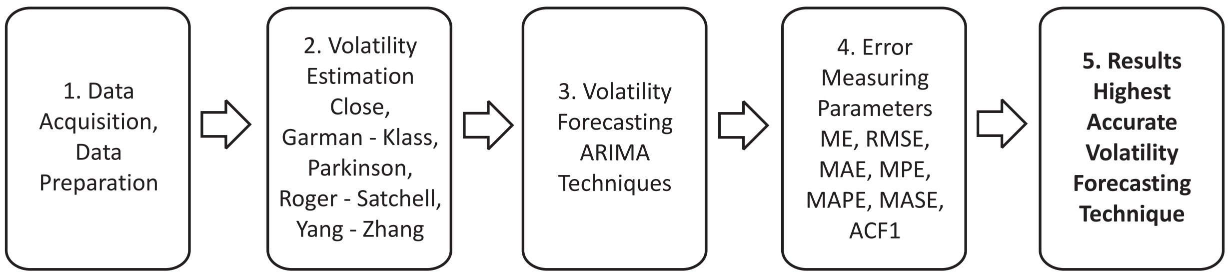
H_i = highest price for the day,

L_i = lowest price of the day,

C_i = evening closing price.

All the prices are for trading days $i = 1, 2, 3 \ldots N$.

Table 1. Methodology to Estimate and Forecast Volatility



The research approach adopted for estimating and forecasting volatility is explained in Table 1.

(1) Volatility Estimation : There are different categories of volatility, namely implied volatility, historical volatility, and realized volatility. In this study, historical volatility is calculated from five different volatility estimators. Generally implied volatility and historical volatility of an asset are compared in order to find if the asset is currently undervalued or not. Different volatility estimators used for this study are as follows :

(i) Close - to - Close : The most fundamental and simple measure of volatility is close-to-close method which is calculated by standard deviation of the closing prices. The following formula is used for estimating volatility by close-to-close method. It assumed zero drift (average return or expected return) :

$$Volatility_{close} = \sigma_{cc} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (Ln\,(\frac{C_i}{C_{i-1}}))^2}$$

(ii) Parkinson : In 1980, the first volatility estimator other than close-to-close method was estimated by Parkinson. Parkinson volatility estimator uses the low and high price which makes it less efficient because of trading hour differences. It underestimates the volatility value - it cannot handle initial jumps and considers only a day's highest and lowest price. The advantage of Parkinson volatility estimator is that the calculated volatility will remain same, irrespective of different exchange locations of the traded security/index (CNX Nifty Index in this study). The formula for estimating volatility is given below :

$$Volatility_{Parkinson} = \sigma_p = \sqrt{\frac{1}{N} \frac{1}{4\ln(2)} Ln\,(\frac{h_i}{l_i})^2}$$

(iii) Garman - Klass : In the late 1980, Garman & Klass advanced a volatility estimator which was an extension of Parkinson volatility estimator. Garman - Klass estimator considered the open and close prices beside high and low prices for the trading day. This estimator is more accurate for estimating volatility because it uses the Brownian motion instead of standard deviation. Brownian motion considers zero drift and there are no opening jumps. As the literature explains, Garman - Klass estimator is 7.4 times accurate than the close-to-close estimation method. The following formula is used for estimating volatility by the Garman - Klass method :

$$Volatility_{Garman\text{ - }Klass} = \sigma_{GK} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [\frac{1}{2}(Ln\,(\frac{h_i}{l_i}))^2 - (2Ln\,(2)-1)\,(Ln\,(\frac{c_i}{o_i}))^2\,]}$$

(iv) Roger - Satchell : In 1991, Roger and Satchell developed an algorithm for estimating volatility and used open, high, low, and close prices. Roger - Satchell volatility estimator also assumed no opening jumps which again led to underestimation of volatility. The advantage of Roger - Satchel volatility estimator was it considered non - zero drift (average return) unlike previous developed volatility estimators which assumed the drift is zero. The formula for the Roger - Satchell volatility estimator is given below :

$$Volatility_{Roger\ -\ Satchell} = \sigma_{RS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\{Ln\left(\frac{h_i}{c_i}\right)Ln\left(\frac{h_i}{o_i}\right) + Ln\left(\frac{l_i}{c_i}\right)Ln\left(\frac{l_i}{o_i}\right)\right\}}$$

(v) Yang - Zhang : In 2000, Yang and Zhang derived a volatility estimator which handled opening jumps. This volatility estimator was found to be 14 times more accurate than close-to-close method as it was independent of the drift. It is formulated as the sum of close-to-open volatility and the weighted average of open-to-close volatility and Roger - Satchell volatility. The following formula is used for estimating volatility by the Yang - Zhang method :

$$\text{Volatility}_{Yang\ -\ Zhang} = \sqrt{\sigma^2_{overnight\ volatility} + k\sigma^2_{open\ to\ close\ volatility} + (1 - k)\,\sigma^2_{RS}}$$

where,

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}$$

$$\sigma^2_{overnight\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[Ln\frac{O_i}{C_{i-1}} - Ln\overline{\frac{O_l}{C_{l-1}}}\right]^2$$

$$\sigma^2_{open\ to\ close\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[Ln\frac{C_i}{O_i} - Ln\overline{\frac{C_l}{O_l}}\right]^2$$

$$\sigma^2_{RS} = \frac{F}{N}\sum_{i=1}^{N}\left\{Ln\left(\frac{h_i}{c_i}\right)Ln\left(\frac{h_i}{o_i}\right) + Ln\left(\frac{l_i}{c_i}\right)Ln\left(\frac{l_i}{o_i}\right)\right\}$$

(2) Volatility Forecasting : The investments related to stock market involve huge risk as a result of which forecasting volatility plays a prime role in financial applications and among stock traders. Based on type of investments, players in the stock market need low volatility as well as high volatility. Knowing volatility in advance can help investors in planning their investments. In this research, volatility is estimated by different volatility estimators. Estimated volatility is used to forecast the volatility by using time series technique named ARIMA. The research examines the best volatility estimator for forecasting through ARIMA, which gives low value for error measuring parameters. The latest trend in research related to forecasting suggests time series techniques forecast more accurately.

The auto regressive integrated moving average (ARIMA) technique was developed by Box and Jenkins from the ARMA model. The importance of ARIMA model under Box - Jenkins methodology is not on constructing the simultaneous equations or single equations but on analyzing the stochastic or probabilistic properties of time series data under the philosophy "let the data speak for themselves" (Gujarati, Porter, & Gunasekar, 2009). ARIMA (p, d, q) model includes three components, namely, (a) AR (autoregressive) component defined by p, (b) Integrated component defined by d, (c) MA (moving average) component defined by q. In order to get the best order to get the best estimate and accuracy of the ARIMA model in forecasting, the estimation and implementation was conducted in RStudio.

Data Analysis and Results

Historical or realized volatility estimation is done by measuring the degree of variation of asset prices returns over time. Among different volatility estimators for volatility, close-to-close, Parkinson, Garman - Klass, Rogers - Satchell, and Yang - Zhang volatility estimators have been used for estimating volatility.

Close-to-close is calculated through the standard deviation of logarithmic difference of inter-day close price of CNX Nifty Index. The plot for volatility estimated by close-to-close method for CNX Nifty Index is shown in the Figure 1. The plot clearly shows the highly volatile behaviour of NIFTY during 2007 - 2009 as calculated by traditional close-to-close method and further giving the stabilizing effect. While few peaks are seen afterwards as well, but still, overall, it can be considered as stable in comparison to its behaviour before 2009.

Parkinson estimator is calculated by using the logarithmic difference of intra-day high and low CNX Nifty Index. After estimating volatility by Parkinson estimator, Parkinson estimation efficiency is calculated and it is found to be 11.91 as maximum and 0.86 as mean. Parkinson estimation is compared with traditional close-to-close estimation.

The plot for Parkinson estimation comparison chart for CNX Nifty Index is shown in the Figure 2. Grey lines describing the Parkinson estimation of volatility show less volatile behaviour in comparison to close-to-close estimation. In between July 2012 and January 2013, a spike shown by grey line can be described as some kind of sudden change in high and low prices on a day in the CNX Nifty Index, which was not taken into consideration by close-to-close estimation.

Garman - Klass estimator is calculated by using logarithmic differences of intra-day open, high, low, and close prices of CNX Nifty Index. After estimating the volatility by Garman - Klass estimator, the efficiency for Garman - Klass estimation is calculated. The maximum variance explained by the estimator is 16.06, and the mean value for efficiency is 0.85, which can also be interpreted as the maximum performance of the estimator against the close-to-close method ("idealized distribution"). The plot for comparison of volatility estimated by Garman - Klass method and close-to-close for CNX Nifty Index is shown in the Figure 3. The plot explains the volatility estimation by Garman - Klass estimator in grey lines, which is less volatile in comparison to close-to-close estimate. The Garman - Klass estimate also explains an intraday sudden change between July 2012 to January 2013 by a spike which was not explained in close-to-close.

Figure 1. Volatility Estimated by Close-To-Close

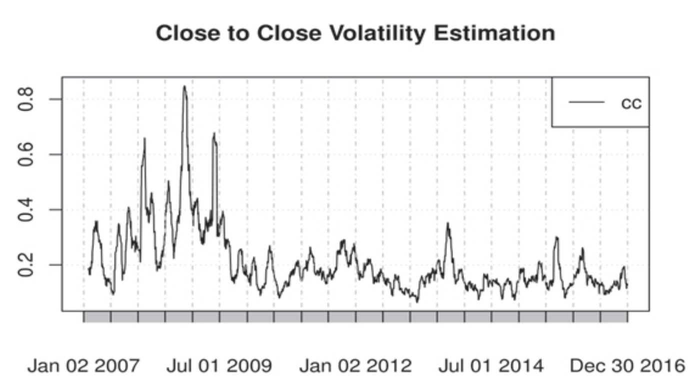


Figure 2. Comparison Chart for Volatility Estimated by Parkinson Estimator and Close-to-Close

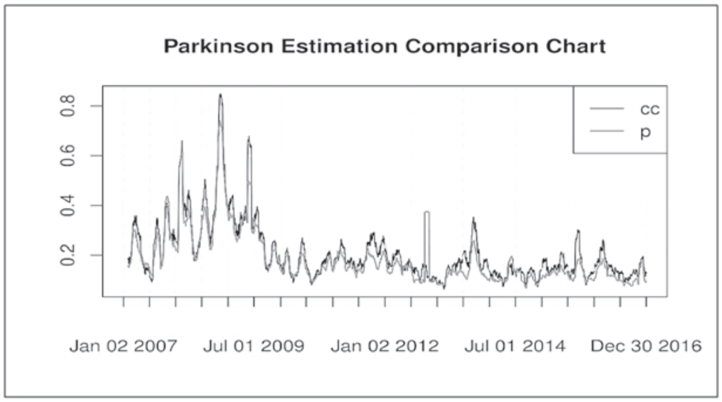
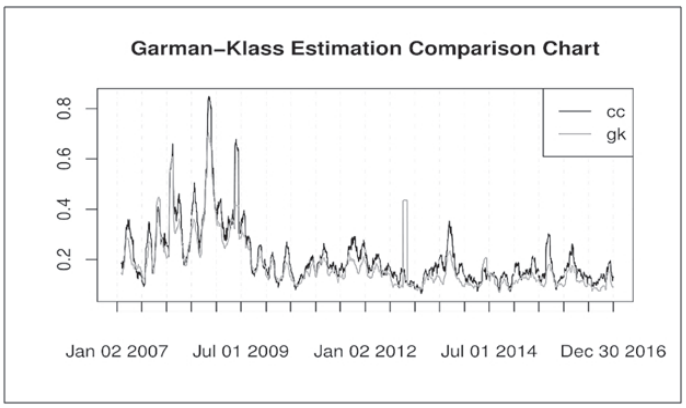


Figure 3. Comparison Chart for Volatility Estimated by Garman - Klass Estimator and Close-To-Close



Rogers - Satchell estimator is calculated by using logarithmic difference of intra-day high, low, open, and close prices for Nifty Index. After estimating volatility by Rogers - Satchell estimator, the efficiency for Rogers - Satchell estimation is calculated. The maximum value for efficiency calculated is 29.22 and the mean value for efficiency is 0.93. Rogers - Satchell estimation values are compared with close-to-close estimation for CNX Nifty Index and the same have been plotted in the Figure 4. The plot explains the volatility estimated by Rogers-Satchell estimator in grey lines, which shows less volatile behaviour in comparison to close-to-close estimate. Rogers - Satchell estimate also explains an intraday sudden change from July 2012 to January 2013 by a spike which was not explained in close-to-close estimation.

Yang - Zhang estimator is calculated by using logarithmic differences of intra-day open, high, low, and close price of CNX Nifty Index. After estimating volatility, efficiency for Yang-Zhang estimation is calculated. The maximum value for the efficiency for this estimator is 25.58 and the mean value for efficiency is 1.109, which can also be interpreted as the maximum performance of the estimator against the close-to-close method. The plot for comparison of volatility estimated by Yang - Zhang estimation and close-to-close for CNX Nifty Index is shown in the Figure 5. The plot explains the volatility estimation by Yang - Zhang estimator in grey coloured lines. The Yang - Zhang estimate also explains an intraday sudden change from July 2012 to January 2013 by a spike which was not explained in close-to-close.

Figure 4. Comparison Chart for Volatility Estimated by Rogers - Satchell Estimator and Close-to - Close

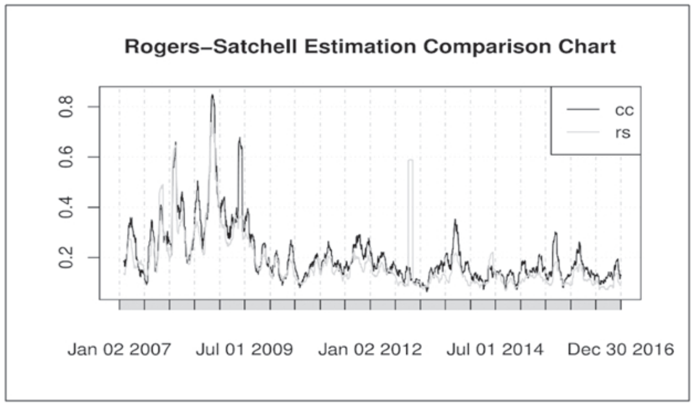


Figure 5 . Comparison Chart for Volatility Estimated by Yang - Zhang Estimator and Close - to - Close

The volatility estimates for different estimators are compared with the close-to-close estimation for checking the performance of various estimators. The results are tabulated in the Table 2. The least values of errors have been marked in bold. The results significantly suggest that different volatility estimators over the traditional close-to-close method will be beneficial for estimating the volatility.

Bias is steady change from the mean, also known as mean error. Bias is calculated as the mean of the differences between the estimated values by extreme value estimators and the traditional close-to-close estimation. Thus, it gives the view whether the estimation method underestimates or overestimates the close-to-close estimation. Relative bias is scaled measure for bias by dividing through the close-to-close estimation. The Table 2 shows that

Table 2. Performance of Volatility Estimators

Estimator	Bias	Relative Bias	Mean Square Error	Mean Absolute Difference
Parkinson	-0.0001707	-1.0026674	**0.0001095**	**0.0078747**
Garman - Klass	-0.0001721	-0.9887384	0.0001095	0.0078752
Roger - Satchell	-0.0001664	-0.9873768	0.0001098	0.0078807
Yang - Zhang	**-0.0001382**	**-0.9848456**	0.0001098	0.0078808

the Yang - Zhang estimator gives a lower value for bias as well as for relative bias. Thus, the Yang - Zhang estimator can precisely estimate the volatility in comparison to other estimators.

Mean absolute difference (MAD) is the absolute value of the bias and is calculated to get the directionless bias in order to know the magnitude of the bias. MAD gives the extent of error in estimating volatility by the estimator in comparison to the traditional close-to-close estimation method (true value). Mean square error (MSE) is the accuracy measure which is calculated by mean differences. It gives the extent of closeness of estimation by the estimator with respect to the close-to-close estimation. All the volatility estimators are efficient based on the performance criteria of MSE and MAD, but Parkinson estimator shows the least values for MSE and MAD, thus making it more efficient among other estimators.

Historical or realized volatility forecasting is done through models, which capture its clustering or inertia and mean - reversion. The model studied for this study is the ARIMA model. ARIMA forecast is used to specify the conditional mean of a process. The main research objective of this work is to examine different volatility estimators and computing the accuracy of the forecasting by using the ARIMA model. After estimating volatility by different volatility estimation methods, training data set was prepared, so that based on it, the ARIMA model can be forecasted and henceforth, the accuracy of that forecasted model can be ascertained. Volatility forecasting accuracy is evaluated on which model minimizes the residuals or forecasting errors based on scale-dependent and scale-independent measures. As a result, six error measuring parameters were computed as accuracy function in RStudio and tabulated in the Table 3. The error measuring parameters are defined as follows :

- ME = Mean error,
- MAE = Mean absolute error,
- MAPE = Mean absolute percentage error,
- MPE = Mean percentage error,
- MASE = Mean absolute scaled error,
- RMSE = Root mean square error,
- ACF1 = Autocorrelation of errors at lag 1.

After testing for stationarity by ADF test, the best ARIMA model has been estimated by the auto.arima function and then forecasting the best ARIMA model is done. The summary in Table 3 gives the accuracy by elaborating the error measures. The accuracy for each estimator is calculated with regard to the forecasted values. For different volatility estimators, different ARIMA model was elaborated by Rstudio (summarized in Table 3) for forecasting. We see that MAE is less than the RMSE values in Table 3, which suggests that the actual and forecasted values are nearly the same. Therefore, the ARIMA model can be considered acceptable, and the forecasted values are accurate.

Table 3. Volatility Forecasting Accuracy

Volatility Estimators	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Close-to-Close ARIMA (0,1,0)	**0.00000008**	0.016537	0.007835	-0.222761	3.884662	0.999600	0.007925
Parkinson ARIMA (4,1,0)	0.00000446	**0.012237**	0.004395	**-0.090970**	2.440363	**0.959564**	-0.001562
Garman - Klass ARIMA (2,1,0)	0.00000213	0.013141	**0.004117**	-0.133231	**2.304137**	0.961594	-0.001199
Rogers - Satchell ARIMA (1,1,0)	0.00000078	0.017965	0.004707	-0.237136	2.598335	0.986851	-0.003472
Yang - Zhang ARIMA (2,1,0)	0.00004330	0.016457	0.004873	-0.153814	2.490440	0.973245	**-0.000920**

The least value for errors suggests the model as better than others in comparison. The least value for errors among all the volatility estimators has been marked in bold in the Table 3. From the Table 3, it is observed that among all the estimators, the Parkinson estimator has three lowest error measurements and the Garman - Klass estimator has two lowest error measuring parameters. So, it is concluded that the Parkinson volatility estimator and the Garman - Klass estimator are better than other estimators for forecasting by using the ARIMA model. Hence, it can be stated that the ARIMA model can forecast better with the Parkinson estimation technique.

Conclusion

Volatility is a fundamental measure for calculating the risks associated with investments. Accurate volatility forecasting, estimating best volatility estimation techniques are required by the players of the stock market. In this study, different volatility estimators like close-to-close, Parkinson, Garman - Klass, Rogers - Satchell, and Yang - Zhang are used for estimating the volatility of the CNX Nifty Index. After estimating volatility, ARIMA model is defined by order (p, d, q) for each estimator for forecasting. Values for p, d, and q are defined as the autoregressive, integrated (difference), moving average terms. Each model is then evaluated with different measures to examine accuracy. In context to practical as well as theoretical studies, the volatility estimators are the efficient estimation tools for volatility. The statement is in-line with the research conducted through this study. The use of volatility estimators is supported by research in the Indian context. There is no significant bias between the estimators with respect to the traditional volatility estimation method. Parkinson estimator is highlighted as the most efficient estimator based on MSE and MAD ; whereas, Pandey (2002) pointed out that Yang - Zhang was an efficient estimator based on MSE and MAD for the S&P CNX Nifty Index. Parkinson estimator is found to be the most accurate estimator for forecasting volatility of the CNX Nifty Index through ARIMA technique than Garman - Klass estimator, which was highly accurate for ARIMA forecasting technique with respect to volatility of the S&P 500 Index (Kumar & Patil, 2015).

Research Implications and Limitations of the Study

In order to enhance investment decisions and manage risks associated with various tradable instruments in the Indian stock market, efficient volatility forecasting is an invariable need. Across the globe, lots of studies have been conducted for accuracy of various forecasting techniques related to volatility. These studies concluded the results which are specific to various constraints like market, forecast time period, estimation methods, etc. The findings of this study suggest that the traders, option practitioners, and investors should take in consideration the logarithmic difference of high and low for estimating volatility for CNX Nifty Index to forecast the volatility compared to any other volatility estimator studied. The advantage of Parkinson volatility estimator is that the calculated volatility will remain the same irrespective of different exchange locations of the traded security/index (CNX Nifty Index in this study). In view of this, stock exchanges must think about introducing India VIX as a trading instrument to hedge the risk involved against investing in the CNX Nifty Index. This in turn would give efficient estimation and forecasts for volatility which would lead to efficient options market for India.

During this study, we studied volatility estimation techniques and volatility forecasting and some questions became evident which could be investigated in future research. Among the family of ARMA models, ARIMA model is analyzed in this study. There are various other models like ARFIMA, SARIMA which could have been analyzed for forecasting as they consider the functional differencing and seasonal effect. Expanding this kind of evaluation might lead to finding a more accurate forecasting model for volatility.

Scope for Further Research

Forecasting time-series for financial data like assets, indices, and various portfolios is a unified requirement for decision making in numerous activities like trading strategies and risk management. The future forecast of volatility for various assets, indices, and portfolios for few next days can help the portfolio managers, traders, and investment advisors in implementing the relevant strategies prevailing in the stock market. The major contribution of this study is that it unveils the accuracy of forecasted values of various volatilities and efficiency of different volatility estimators. The forecasted values for various estimators are tabulated in the Appendix (the forecasted values of Close-to-Close, Parkinson, Garman - Klass, Rogers - Satchell, Yang-Zhang estimators are tabulated in Appendix Table 1A, Appendix Table 1B, Appendix Table 1C, Appendix Table 1D, and Appendix Table 1E, respectively), which can be studied further for future research in accuracy or forecasting or error estimation. However, there is further scope of validating the various models of ARIMA by testing them on different time horizons. Secondly, using more advanced methodologies like artificial neural networks can bring more unrevealed evidence about the volatility of the Indian stock market.

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Appendix

Appendix Table 1(A). Forecast Results for Volatility Using Close-to-Close Estimation Method in ARIMA Model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2475	0.1858454	0.1648201	0.206871	0.15369	0.218001
2476	0.1858461	0.1561118	0.21558	0.140371	0.231321
2477	0.1858468	0.1494299	0.222264	0.130152	0.241542
2478	0.1858474	0.1437968	0.227898	0.121537	0.250158
2479	0.1858481	0.1388341	0.232862	0.113946	0.25775
2480	0.1858488	0.1343475	0.23735	0.107084	0.264613
2481	0.1858495	0.1302217	0.241477	0.100774	0.270925
2482	0.1858501	0.1263816	0.245319	0.094901	0.276799
2483	0.1858508	0.1227749	0.248927	0.089384	0.282317
2484	0.1858515	0.1193636	0.252339	0.084167	0.287536

Appendix Table 1(B). Forecast Results for Volatility Using Parkinson Estimation Method in ARIMA Model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2475	0.1710396	0.1554718	0.186607	0.147231	0.194849
2476	0.1711137	0.1468873	0.19534	0.134063	0.208165
2477	0.1712134	0.1399885	0.202438	0.123459	0.218968
2478	0.1712592	0.1338378	0.208681	0.114028	0.22849
2479	0.1712819	0.1278795	0.214684	0.104904	0.23766
2480	0.1712967	0.1223979	0.220196	0.096512	0.246081
2481	0.1713087	0.1173613	0.225256	0.088803	0.253814
2482	0.1713155	0.1126814	0.22995	0.081642	0.260989
2483	0.1713193	0.1082895	0.234349	0.074924	0.267715
2484	0.1713217	0.1041552	0.238488	0.068599	0.274044

Appendix Table 1(C). Forecast Results for Volatility Using Garman - Klass Estimation Method in ARIMA Model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2475	0.1506705	0.13396012	0.1673808	0.125114	0.176227
2476	0.1506827	0.12475695	0.176608	0.111033	0.190333
2477	0.1506873	0.11729222	0.184082	0.099614	0.201761
2478	0.1506886	0.11102568	0.190352	0.090029	0.211348
2479	0.1506891	0.10556806	0.19581	0.081682	0.219696
2480	0.1506892	0.10068772	0.200691	0.074219	0.22716
2481	0.1506892	0.09623875	0.20514	0.067414	0.233964
2482	0.1506893	0.09212554	0.209253	0.061124	0.240255
2483	0.1506893	0.08828248	0.213096	0.055246	0.246132
2484	0.1506893	0.08466261	0.216716	0.497102	0.251668

Appendix Table 1(D). Forecast Results for Volatility Using Rogers - Satchell Estimation Method in ARIMA Model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2475	0.1370199	0.11417854	0.159861	0.102087	0.171953
2476	0.1370181	0.1027629	0.171273	0.084629	0.189407
2477	0.1370179	0.09410696	0.179929	0.071391	0.202645
2478	0.1370179	0.08690599	0.18713	0.060378	0.213657
2479	0.1370179	0.08061503	0.193421	0.050757	0.223279
2480	0.1370179	0.07495833	0.199077	0.042106	0.23193
2481	0.1370179	0.06977581	0.20426	0.03418	0.239856
2482	0.1370179	0.06496508	0.209071	0.026823	0.247213
2483	0.1370179	0.06045604	0.21358	0.019927	0.254109
2484	0.1370179	0.05619818	0.217838	0.013415	0.260621

Appendix Table 1(E). Forecast Results for Volatility Using Yang - Zhang Estimation Method in ARIMA Model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2475	0.2742122	0.2532883	0.295136	0.242212	0.306213
2476	0.27421	0.2423428	0.306077	0.225473	0.322947
2477	0.2742102	0.2335487	0.314872	0.212024	0.336397
2478	0.2742102	0.2261879	0.322232	0.200767	0.347654
2479	0.2742102	0.2197729	0.328647	0.190956	0.357465
2480	0.2742102	0.2140279	0.334393	0.182169	0.366251
2481	0.2742102	0.2087828	0.339638	0.174148	0.374273
2482	0.2742102	0.2039274	0.344493	0.166722	0.381699
2483	0.2742102	0.1993862	0.349034	0.159777	0.388644
2484	0.2742102	0.1951052	0.353315	0.15323	0.395191

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