Modeling Volatility Clustering of Bank Index: An Empirical Study of BankNifty

Review of Integrative Business & Economics Research

Ashok Patil*
Kirloskar Institute of Advanced Management Studies

Gita Madhuri
Kirloskar Institute of Advanced Management Studies

Bidyanand Jha
Kirloskar Institute of Advanced Management Studies

ABSTRACT

Time series of asset-returns often exhibit volatility clustering, and it has been observed that volatility in indices are clustered too. Volatility determines the risk-profile of an index and in-turn the payoffs of derivative positions on those indices. The objective this paper is to capture the presence of volatility clustering and model the volatility profile over a period of 10 years of BankNifty index. BankNifty index represents the twelve most liquid and large capitalized stocks from the banking sector, which trades on National Stock Exchange of India. For the purpose of this study, the daily closing indices were transformed to daily log-returns to make the series stationary so that ARIMA and GARCH models could be fit on the data. This paper finds that volatility clusters exist in log-returns of BankNifty and fits ARIMA (0, 0, 1) and GARCH (1, 1) model on log-returns of BankNifty data collected from April 2005 to March 2016. The findings of this paper help derivative bank-index traders to take rational investment decisions. It also confirms the existence of volatility clustering in bank-index and provides a model that fits the log-returns of BankNifty during the study period.

Keywords: Bank index, volatility, clustering, ARIMA, GARCH.

1. INTRODUCTION

1.1. Asset Returns and Volatility Clustering

Volatility in stock returns has attracted attention of many investors especially post financial crisis of 2008. Statistical properties of stock returns, indices, volatility have been studied pre- financial crisis; however, availability of large data sets with high frequency price series and intensive computer applications has enabled the researchers and investors to study the financial properties including volatility in a pragmatic manner.

A set of properties common across many instruments, markets and time series has been observed by independent studies and classified as stylized facts. The stylized facts of financial assets state that the returns on financial assets show insignificant autocorrelations – hence are difficult to predict – and have fat-tailed distributions,

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

whereas volatility in returns exhibit a positive autocorrelation over several days demonstrating presence of 'volatility clustering'. Cont R (2005), Pesaran, M Hasham (2010). Understanding volatility clustering is essential from a trader's investment perspective as it impacts the returns on her portfolio. Therefore, understanding stylized empirical facts become imperative in order to implement an effective risk management strategy. The impact of clustering is more prominent for the investors in derivative instruments as they are highly leveraged.

Volatility refers to the amount of uncertainty or risk in the value of the security over a period of time. A higher volatility refers to a wide range of changes in the value of the security and lower volatility refers to lesser fluctuations in the change of values over a period of time. Volatility in time series of stock market returns exhibit volatility clustering i.e. volatility varies with time and clusters of low volatility and high volatility are observed over a period. Generally time series are found to be autoregressive i.e. present values are dependent on their past values and are heteroscedastic i.e. they exhibit conditional stochastic variances over a period.

Mandelbrot (1963) noted that 'large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes'. Rama Cont (2005) indicated that 'the quantitative manifestation of this fact is that, while returns themselves are uncorrelated, absolute returns or their squares display a positive, significant and slowly decaying autocorrelation function ranging from a few minutes to several weeks'.

The classical linear regression model assumes that residuals are homoscedastic, while in the case of financial time series the residuals are heteroscedastic. This fact makes stochastic models such as ARCH/GARCH more appropriate and relevant for modeling volatility clustering. Engle (1982) introduced ARCH to model time varying conditional variance and Bollerslev (1986) introduced a generalized ARCH (GARCH) model for measuring stochastic volatility. This paper applies GARCH model to account for volatility clustering in BankNifty index.

1.2. Banking Sector Scenario in India

The total Indian banking sector assets increased at CAGR of 8.2% to $1.5 trillion during financial year 2010-12 and deposits grew at CAGR of 21.2% during financial years 2006-13. (M Narendra, CMD, Indian Overseas Bank, Source: Survey of Indian Industry, The Hindu, 2014). According to World Bank report Indian Banking sector is assessed being on a high growth trajectory with around 3.5 ATMs and less than 7 bank branches per 100,000 people. KPMG-CII report says that the Indian banking sector is expected to become 5th largest in the world by 2020.

"The future of banking in India looks not only exciting but also transformative, banks remain the largest financial sector intermediary in India. In future technology will make the engagement with banks more multi-dimensional even as other entities, markets, and instruments for credit and financial services continue to develop and expand. As India's integration with the global economy increases and the rupee gets internationalized, Indian banks will facilitate corporate access to offshore markets and

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

capital pools. Managing risk will become increasingly important and technology and analytics will become the cornerstones of improved risk management in the country. Banks will be the institutions that provide an array of financial services to customers in this volatile and uncertain competitive environment.” (Source: Livemint)

BankNifty represents the twelve most liquid and capitalized stocks from the banking sector which trade on NSE, which provides investors and market intermediaries a benchmark that captures the capital market performance of Indian banking sector. As on 29th July 2016, the total volume of BankNifty Derivative contracts is 5, 91, 682 totaling to a value of 45,266.81 crores with an underlying BankNifty index value of 18,740.60. It is interesting to note that the volume traded on BankNifty is about 30% of the average daily turnover of index f & o segment in 2015-16. (Source: NSE India)

1.3. Objectives of the Study

Investment advisors or traders in derivative instruments with bank-index underlying are exposed to volatility risks in the short run and would like to take rational position to minimize the portfolio risk.

The objective of this study is

a. To verify the existence of volatility clustering in the BankNifty index
b. To model the volatility phenomenon by fitting an appropriate ARCH/GARCH model for the period between financial years 2005 and 2016.

2. LITERATURE REVIEW

Samuelson (1965) advanced the random walk of theory of asset prices upon which Efficient Market Hypothesis (EMH) was based. The EMH states that price changes in efficient markets – that incorporate all the information available at the moment – are random and unpredictable. Kendall (1953), Cowels (1960), Osborne (1959), Osborne (1962) and Fama (1965) have provided statistical evidences on the random nature of equity prices. However, Chudik, Pesaran and Tosetti (2010) showed that the efficient market theory need not hold in markets populated with risk-averse traders, even under market efficiency. It is also seen that although the return of assets are uncorrelated and show evidence for ‘random walk’, the non-autocorrelation does not imply independence. The absolute or squared returns show significant positive autocorrelation in the risk of the return series. This significant positive autocorrelation of risk is a well-known phenomenon called ‘volatility clustering’: Large variations are likely to be followed by large variations. Volatility clusters in return series is generally corrected using ARCH/GARCH models and hence become predictable. Cont R (2005)

Gertler and Hubbard (1988) revealed in their research work that the investment business spending is influenced by the volatility in stock returns. Schwert (1989 and 1990) in his research works modeled the changes in volatility in stock market. Karmakar (2006) emphasized the need for volatility modeling for financial risk management, pricing of options, etc. by measuring the daily stock return volatility. The research work of Joshi and Pandya (2000) studied the volatility using GARCH

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

models on Indian stock markets to understand the turbulence, and observed that volatility has an important impact on earnings of individual investors and also on stock market efficiency.

ARCH technique introduced by Engle (1982) has been implemented for modeling volatility in financial markets, and its success has led to extensive literature by Bollarslev, et al. (1986, 1993, 1996) that could generalize the result using GARCH model to other financial instruments. Although there are some studies of Brooks & Hinich (1998) showing that GARCH model or its any variant cannot capture all the statistical structures that are present in the data, the model has been since used in the literature to capture the volatility in the financial instruments.

Anderson et al. (2001) found that increasing the frequency of intra-day observations improves the accuracy of the forecasts based on the GARCH models.

3. DATA ANALYSIS AND FINDINGS

All the analysis in this paper has been done using free software R.

3.1. Data

The data for this study was collected from www.aceanalyser.com on the daily closing indices of BankNifty index for the period starting from 01-04-2005 to 31-03-2016. The prices were converted to time series data and plot in Figure 1 shows that the series of indices shows an increasing trend.

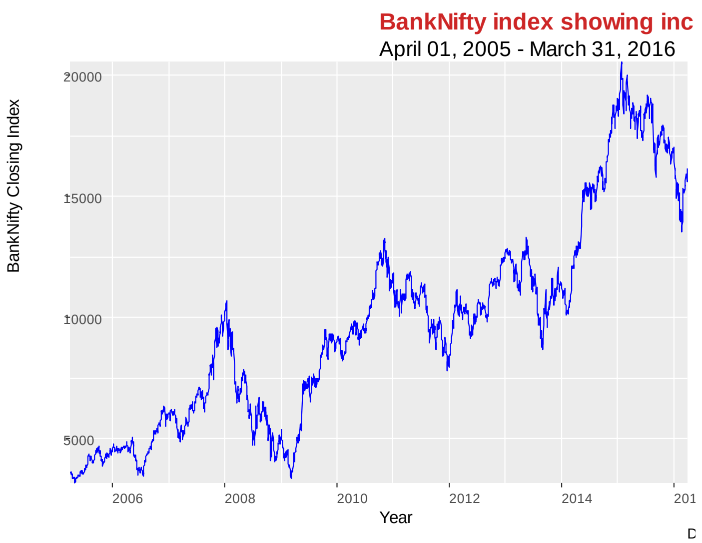

Figure 1

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

KPSS test results in Table 1 also confirm the presence of trend in the series.

Table 1

KPSS Trend Stationarity Test	
Data	BankNifty Index
KPSS trend	0.96986
Truncation Lag Parameter	12
p-value	0.01
Null hypothesis	Trend stationary

Therefore, it is necessary that the data be transformed using appropriate transformation methods to use the data for further analysis.

3.2. Data Transformation

The ACF and PACF plots in Figure 2 of the BankNifty index indicate that autocorrelations are high for many lags and therefore, differencing in the series is required before any further analysis is conducted.

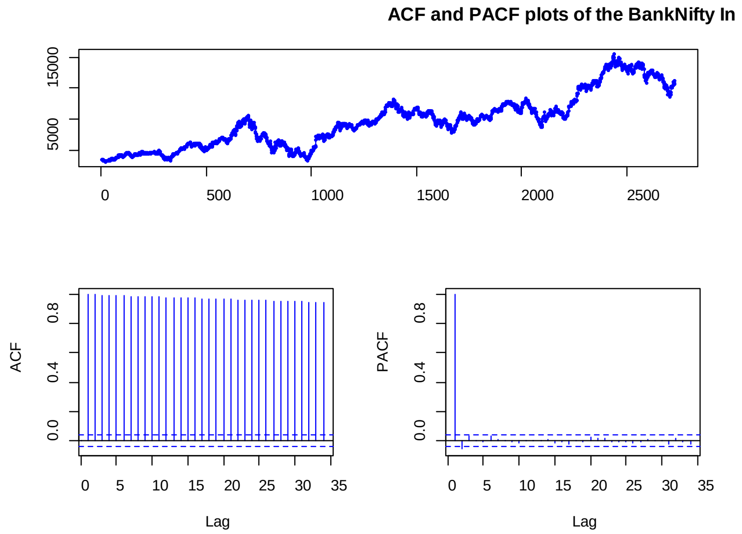

Figure 2

As such, the financial returns are calculated on the continuously-compounded basis, which is calculated by taking difference of log indices. Therefore, the indices were log transformed and then taken first differences to obtain daily continuously-compounded log-returns of indices. Figure 3 shows the log-returns of indices.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

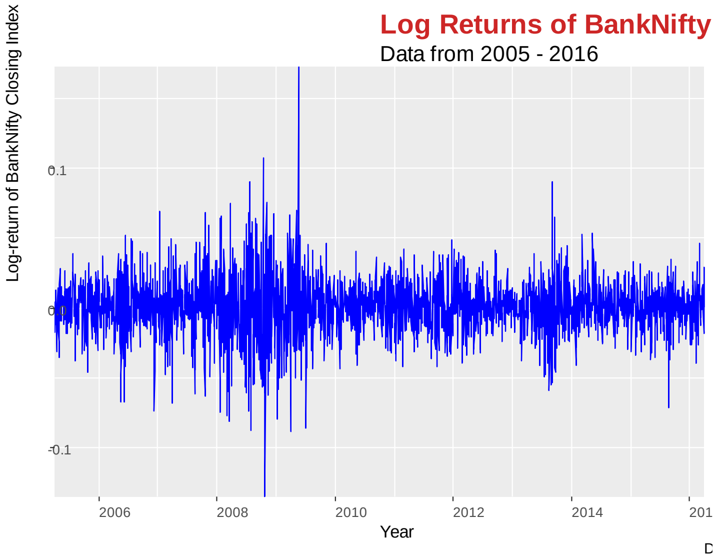

Figure 3

Having transformed that data, it is necessary to check for the stationarity of the series before ARIMA model is employed. It is thus verified that the data is stationary using Augmented Dickey-Fuller Test. The test results in Table 2 indicate that the log-returns of BankNifty index are stationary.

Table 2

Augmented Dickey-Fuller test	
Data	Log-returns of BankNifty Index
Dickey-Fuller	-13.226
Lag order	13
p-Value	0.99
Alternative Hypothesis	Explosive

Table 3 summarizes the results KPSS test on the data and confirms that there is no trend in the log-returns of the BankNifty index as well.

Table 3

KPSS Test for Trend Stationarity	
Data	Log-returns of BankNifty Index
KPSS Trend	0.03065
Truncation lag parameter	12
p-Value	0.1

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

Autocorrelation function and partial autocorrelation function of log-returns of BankNifty index are shown in Figure 4 also confirm that no further differencing is required and statistical models such as ARIMA can now be applied on this stationary data.

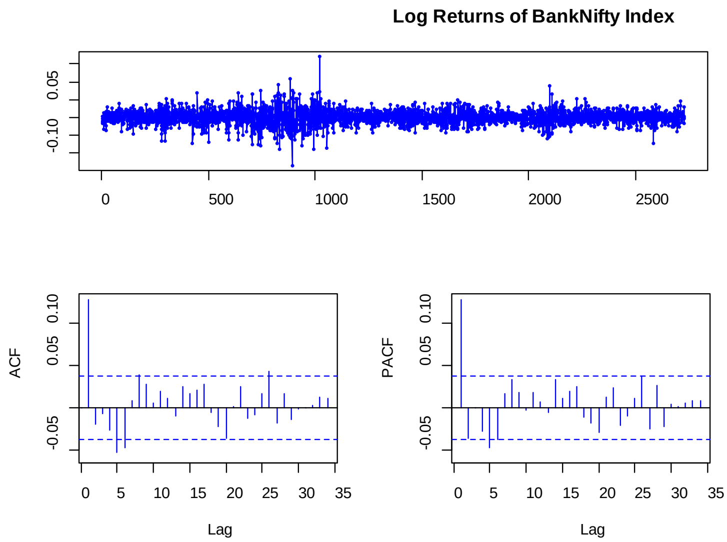

Figure 4

3.3. Data Analysis

3.3.1. Model Fitting: ARIMA

ARIMA models with different parameters of autoregression and moving average were applied to identify the lowest AIC. The lowest AIC was obtained for an ARIMA (0, 0, 1) model on the log-returns of the BankNifty index.

The ARIMA (0, 0, 1) model summary is represented in Table 4 below:

Table 4

	Estimate	Std.Error	t-value	p-value
Lag 1 MA coefficient	0.1345	0.0193	6.9580	0.0000
Intercept	0.0005	0.0004	1.2701	0.2042
AIC	-13639.59			
Sigma^2	0.0003951			

The t-value for Lag 1 MA coefficient rejects the null hypothesis that the coefficient is zero whereas t-value for Intercept fails to reject the null hypothesis indicating that the intercept to be zero.

Post-diagnostics plots of errors of ARIMA (0, 0, 1) model in Figure 5 confirm that the residuals of the model are white noise and follow near normal distribution with flat tails.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

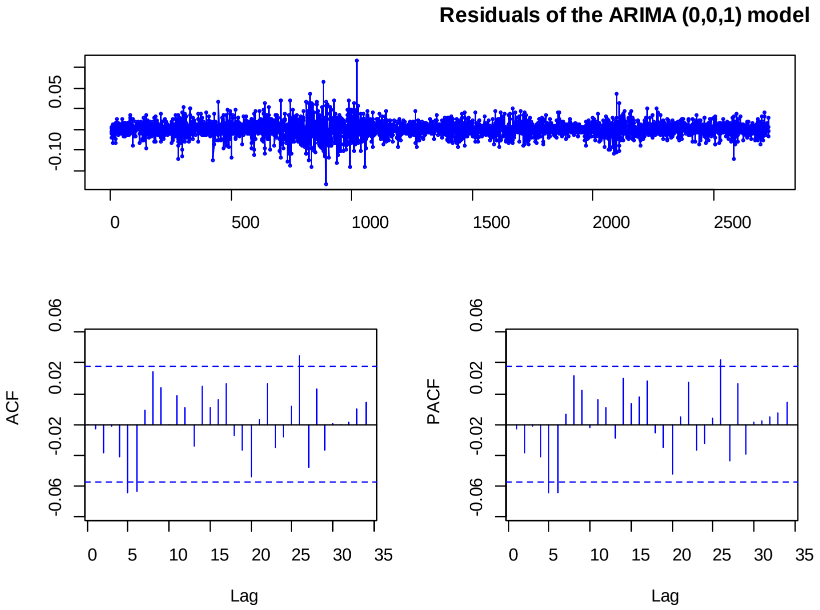

Figure 5

The box plot test results conducted on the residuals of the model in table below show that the returns are independent.

Table 5

Box-Ljung test	
Data	Residuals ARIMA (0, 0,1)
X-squared	28.029
Df	19
p-value	0.08287

Thus post-diagnostic tests confirm that the log-returns of BankNifty index can be modeled using Equation 1 shown below.

Equation 1

$$R = 0.1345 * e_{t-1} + \varepsilon$$

where,
R stands for log-return of BankNifty Index
e stands for lag-1 MA term
ε stands for error terms

This model can be used to forecast the returns of the series. Figure 6 shows the forecast of next 100 days returns with 95% and 99% confidence intervals.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

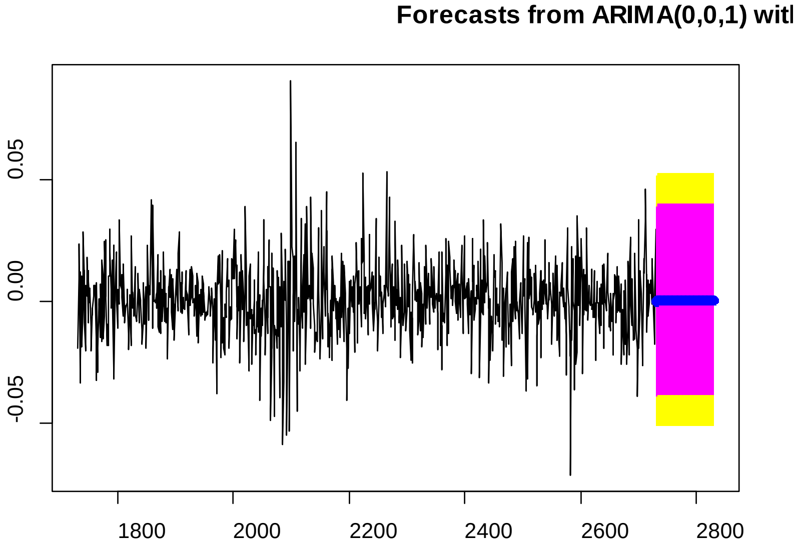

Figure 6

The results of the accuracy of the forecast is captured in terms of Mean Errors (ME), Root Mean Squared Errors (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE). The model requires that these errors be low and the errors are low in the results summarized in Table 6 below.

Table 6

Error Type	Measure
ME	-0.0000001902289
RMSE	0.01987816
MAE	0.01425254
MPE	96.6347
MAPE	127.88
MASE	0.7412909
ACF1	0.002468458

3.3.2. Model Fitting: ARCH/GARCH

As discussed in the literature review, the return of the series shows volatility clustering showing that large changes in volatility are likely to be followed by large changes in volatility. Therefore, it is verified for the presence of volatility clusters in the log-return of BankNifty index. Figure 7 shows volatility measured by the square of residuals.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

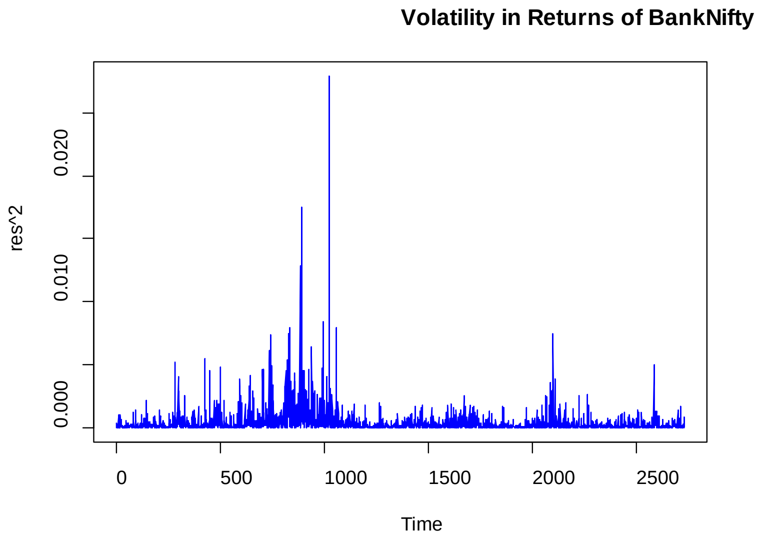

Figure 7

Further, ARCH test is conducted on the residuals to determine whether there are volatility clusters in the data. The test results in the Table 7 below indicate that there are volatility clusters and ARCH models can be applied to the residuals.

Table 7

ARCH LM-test	
Null hypothesis	no ARCH effects
Data	Residuals of ARIMA (001)
Chi-squared	296.21
df	18
p-value	< 0.00000000000000022

Since there are ARCH effects in the residuals of the series, various GARCH models are applied and model with relative function convergence is selected. GARCH (1, 1) provides such a model for the data used for this study. The summary of the results is listed in the Table 8, Table 9 and Table 10 below.

Table 8

Coefficients				
	Estimate	**Std.Error**	**t-value**	**Pr(>|t|)**
a0	0.0000044193	0.0000008469	5.218	0.000000181
a1	0.0645560356	0.0065662295	9.832	< 0.00000000002
b1	0.9240631181	0.0072093701	128.175	< 0.00000000002

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

Table 9

Jarque Bera Test	
Data	Residuals
X-squared	242.7
df	2
p-value	< 0.00000000000000022

Table 10

Box-Ljung test	
Data	Squared residuals
X-squared	0.018407
df	1
p-value	0.8921

Since all the coefficients of the variance model are significant the model on the variance can be presented as in equation 2 below.

Equation 2

$$\sigma_t^2 = 0.0000044193 + 0.06455 * \varepsilon_{t-1}^2 + 0.924 * \sigma_{t-1}^2$$

where
σ^2 is variance of error terms of the series as represented in Equation 1
ε is the autoregressive error term as represented in Equation 1

The following Figure 8 shows that the volatility clustering exist in the series. Conditional variances in the plot exhibit and confirm the stylized facts about the volatility that large changes in variances are likely to be followed by large changes in volatility.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

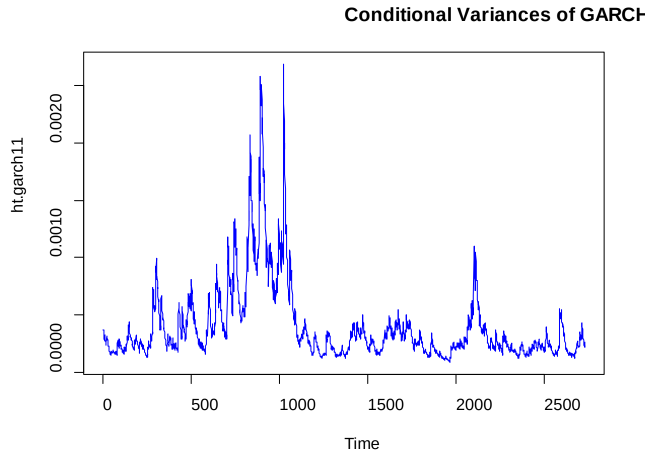

Figure 8

Having fitted the model, the forecasted values using this model are plotted over the in-sample data to visualize the accuracy of the model. The following Figure 9 fits the forecast on the log-returns of the BankNifty index.

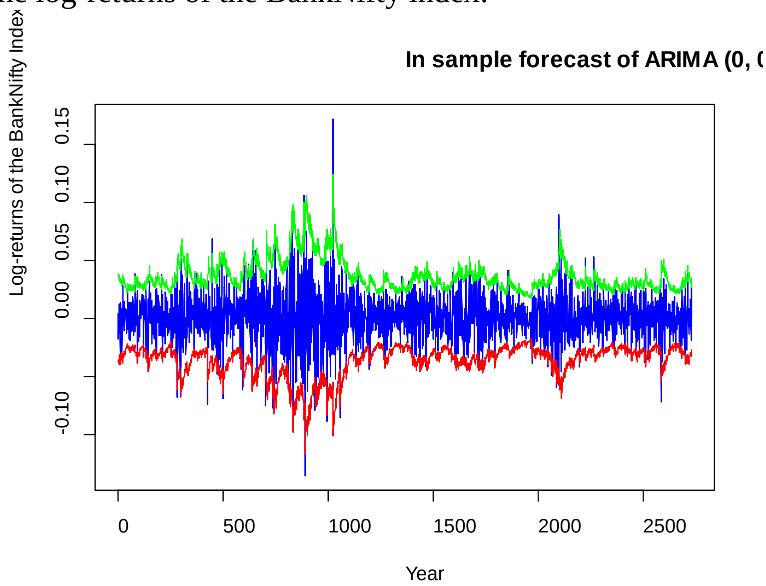

Figure 9

The forecast model snuggly fits the log-returns of the BankNifty index and may be used for predicting the behavior of the index in future.

3.4. Post-Model Diagnostics

However, before finalizing the model, post-model diagnostic tests are conducted on the residuals of the model so that the residuals are white noise and iid random variable.

Figure 10, Figure 11, and Figure 12 above confirm that the residuals of the model are white noise and there is no autocorrelation amongst them.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

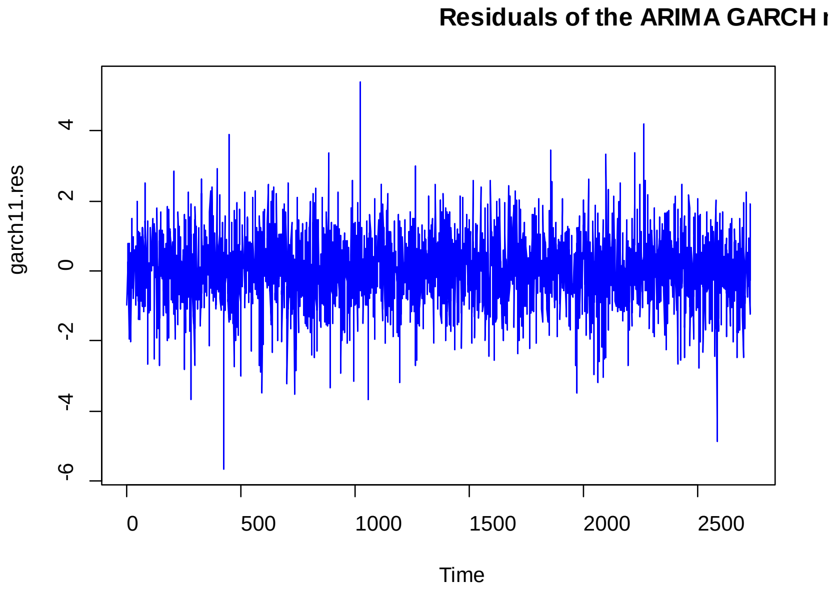

Figure 10

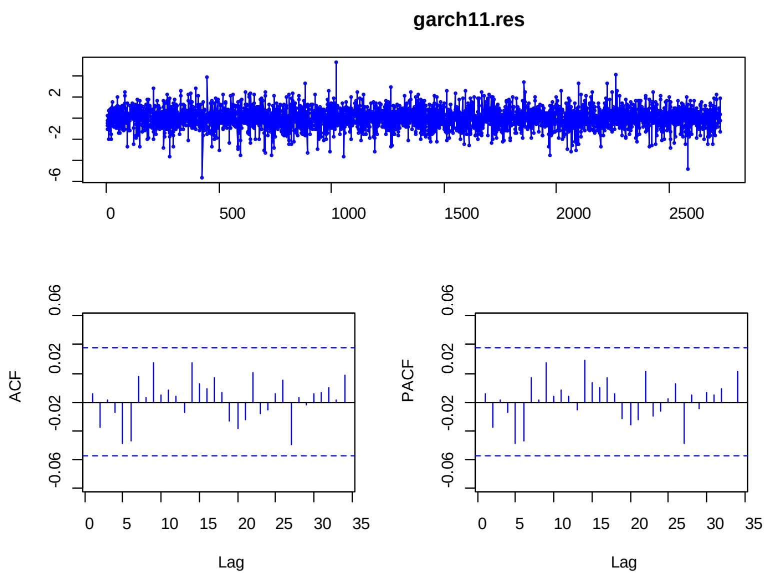

Figure 11

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

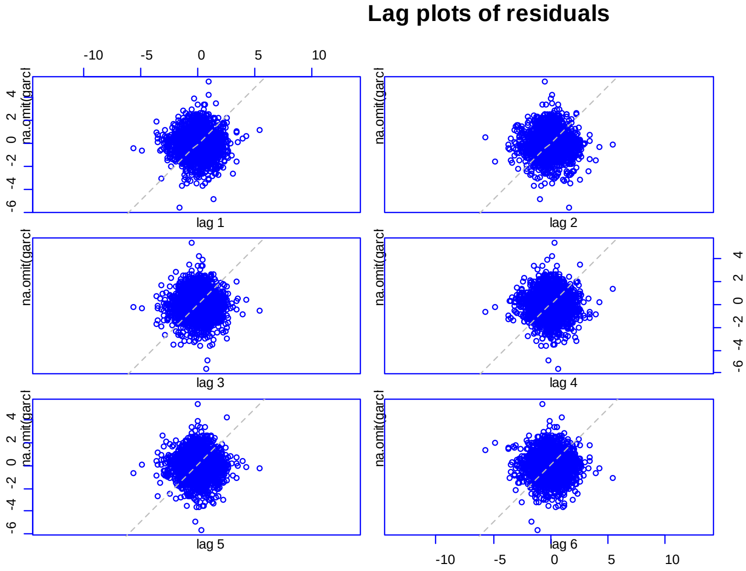

Figure 12

The box test results in Table 11 show that the errors of the model also are independent. Therefore, the post-diagnostic tests accept the model as presented in Equation 1 and Equation 2.

Table 11

Box-Ljung test	
Data	Garch11.res^2
X-squared	3.8691
Df	6
p-value	0.6944

4. CONCLUSION

In this study, presence of volatility clustering of BankNifty index is tested using ARIMA and ARCH/GARCH models. The daily closing prices of BankNifty index for ten years starting from April 01, 2005 to March 31, 2016 was collected and modeled using GARCH model. The unit root tests were conducted before employing ARIMA, and ARCH test was conducted before employing GARCH model. Our study uses extensive post-model diagnostics for acceptance or rejection of the model. The results of the study show that the log-returns of BankNifty index follow ARIMA (0, 0, 1) model and the volatility follows GARCH (1, 1) model. Our findings support the findings of previous research studies of Cont R (2001), Karmakar M (2006).

This study, however, does not include the comparison of various GARCH models such as eGARCH, t-GARCH, etc. for evaluating the best models that explain the volatility. However, previous studies including Zakaria and Winker (2012) and Zivanayi and Chinzara (2012) found GARCH (1, 1) model to be the best model amongst the GARCH family of models for fitting volatility clusters.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

Further study on volatility can be done with the inclusion of other economic variables that may impact the volatility of the bank index such as changing regimes, national income, inflation, change in interest rates, etc. using VAR and VECM models.

REFERENCES

[1] Akgiray, V. (1989), "Conditional Heteroscedasticity in Time-Series of Stock Returns: Evidence and Forecasts", Journal of Business, 62/1, 55-80.

[2] Bekaert, (1995), "Emerging Equity Market Volatility", *Journal of Financial Economics*, 43, 29-77.

[3] Chudik, A., Pesaran, M.H. and Tosetti, E. (2010), "Weak and Strong Cross Section Dependence and Estimation of Large Panels". *Mimeo, University of Cambridge*.

[4] Cont, R. (2001), "Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues", *Quantitative Finance, Institute of Physics Publishing*, 1, 223-236.

[5] Cowles, A. (1960), "A Revision of Previous Conclusions Regarding Stock Price Behavior", *Econometrica*, 28, 909 – 915.

[6] Engle, R. F. and Ng V. K. (1993), "Measuring and Testing the Impact of News on Volatility", *The Journal of Finance*, 48/5, 1749-1778.

[7] Fabozzi, F. J., Tunaru R. and Wu T. (2004), "Modeling Volatility for Chinese Equity Markets", *Annals of Economics and Finance*, 5, 79-92.

[8] Fama, E. F. (1965), "The Behavior of Stock Market Prices", *Journal of Business*, 38, 34-105.

[9] Gertler, M. L., Hubbard, R. G. (1988), "Financial Factors in Business Fluctuations", *NBER Working Paper*, 2758.

[10] Hyndman, R. J. and Athanasopoulos G. (2013), "Forecasting: Principles and Practice". *O Texts.*

[11] Karmakar, M. (2006), "Stock Market Volatility: Roots and Results", *Vikalp*, 20/1, 7-48.

[12] Kaul, G. and Seyhun, N. (1990), "Relative Price Variability, Real Shocks, and the Stock Market", *Journal of Finance*, 45/2, 479–496.

[13] Kendall, M. (1953), "The Analysis of Economic Time Series – part I: Prices", *Journal of Royal Statistical Society*, 96, 11-25.

[14] Kleiber, C., and Zeileis, A. (2008), "Applied Econometrics with R". *Book, Springer Science + Business Media, LLC*.

[15] Live Mint
www.livemint.com/Opinion/RbCdGWKtAKfgyTDXYNEwvK/Banking-in-India-

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

2016-and-beyond.html

[16] Mukhopadhyay, D., Sarkar, N. (January 2003), "Stock Return and Macroeconomic Fundamentals in Model Specification Framework—Evidence from Indian stock Market", *Journal Indian Statistical Institute*.

[17] NSE India https://www.nseindia.com/live_market/dynaContent/live_watch/bn_home_page.htm

[18] NSE India https://www.nseindia.com/products/content/derivatives/equities/historical_fo_bussinessgrowth.htm

[19] Osborne, M. (1959), "Brownian Motion in the Stock Market", *Operations Research*, 7, 145-173.

[20] Osborne, M. (1962), "Periodic Structures in the Brownian Motion of Stock Prices", *Operations Research*, 10, 345-379.

[21] Pesaran, M. H. (2010), "Predictability of Asset Returns and the Efficient Market Hypothesis", *IZA, Institute for the Study of Labor*, D P No. 5037.

[22] R Core Team (2016), "R: A Language and Environment for Statistical Computing", *R Foundation for Statistical Computing, Vienna, Austria*. URL https://www.R-project.org/

[23] Samuelson, P. (1965), "Proof that Properly Anticipated Prices Fluctuate Randomly", *Industrial Management Review*, Spring 6, 41-49.

[24] Schwert, WG. (1989), "Why Does Stock Market Volatility Change Over Time?", *Journal of Finance*, 44/5, 1115-53.

[25] Schwert, WG. (1990), "Stock Market Volatility", *Financial Analysts' Journal*, May-June, 23-34.

[26] The Hindu: http://www.thehindu.com/navigation/?type=static&page=books&name=sii&year=2014&linkname=sii14

[27] Thiripalraju, M., H. Acharya Rajesh (2010), "Modeling Volatility for Indian Stock Market", *ICFAI University Press' Journal of Applied Economics*, 79-105.

[28] Zakaria, S. S. A., and Winker, P. (2012), "Modeling Stock Market Volatility using Univariate GARCH models: Evidence from Sudan and Egypt", *International Journal of Economics and Finance* 4/8, 161-176.

[29] Zivanayi, N. M., and Chinzara, Z. (2012), "Risk Return Tradeoff and Behaviour of Volatility on the South African Stock Market: Evidence from both Aggregate and Disaggregate Data", *South African Journal of Economics*, 80/3, 345-366.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)