PalArch's Journal of Archaeology of Egypt / Egyptology

FINANCIAL MARKET INVESTMENT DECISIONS: PARAMETRIC AND NONPARAMETRIC APPROACH

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Dr. Vidya Bai G, Dr. Suhan Mendon, Mr. Daniel Frank, Dr. Smitha Nayak, Financial Market Investment Decisions: Parametric And Nonparametric Approach-- Palarch's Journal Of Archaeology Of Egypt/Egyptology 17(7). ISSN 1567-214x
KeyWords: Return, Risk, Auto Regressive Conditional Heteroscedastic, General Auto Regressive Conditional HeteroscedasticNon-parametric.
JEL Classification: B23, G00, C14

ABSTRACT

Fluctuations of stock market depends primarily on fundamental and technical factors and is based on the risk and return factors like time, contracts, sudden fluctuations etc., involved in every asset and stock. By modelling and analysing the data which explains the economic phenomena and market trends, the risk of investment can be reduced resulting in higher return. This is very important because the fluctuations in the market can cause huge losses to the individuals as well as the economy of a country. Parametric models like Auto Regressive Conditional Heteroscedastic/ General Auto Regressive Conditional Heteroscedastic and Non-Parametric smoothing techniques are applied to predict the returns and reduce the residuals.

INTRODUCTION

In the field of finance, it's fascinating to monitor price behaviour frequently to realize the possible behaviour of the prices in forthcoming days. Financial activities generate several new issues, economic science provides theoretical foundation, and statistics and arithmetic are essential tools to resolve the quantitative issues in finance. Stock brokers always deal with the risk associated with change in price. The risks are often summarized by the variance of the long run returns or by their association with relevant co variances in a very portfolio context. Predictions of future return's deviations offer the up-to-date indications of risks.

Financial Economics is a lively field that integrates finance, economics, chance, applied math and statistics. A vital component of it is the study of the expected returns and volatilities of the value dynamics of stocks and bonds that are directly concerning quality valuation, proprietary commercialism, security and portfolio management. As for investors, the market price of stocks provides information on performance of varied firms and helps economical investment choices to be created.

ARCH (Auto Regressive Conditionally Heteroscedasticity) models designed to accommodate time-varying risks. The appearance of ARCH model has marked the last 3 decades of Financial Economics and was breakthrough within the means econometricians want to model and judge the returns and risk on assets. Nevertheless, due to their restrictive form, ARCH models fail to account for several empirical features, such as asymmetric response of volatility to rising and falling asset prices and postulate a deterministic relationship between the risk and past returns.

OBJECTIVES

The main objective of the research is to analyse financial time series and model the volatilities of financial data. For this purpose, we have collected the daily stock data of CIPLA Ltd for the year 2018-19 (particularly this year is selected because of price fluctuations in the Pharmaceutical Industry). The existing GARCH model is used for the analysis purpose. It is data driven approach and provides information regarding the key features in the data. The different stages involved in the analysis are:

1. ARCH and GARCH model fit for the return series for a particular company.
2. Estimating Volatility parameter.
3. To determine a volatility model for the return series using non parametric regression.

In this context appropriate MATLAB and R software are used to develop programsto implement the steps involved in the data analysis based on GARCH model approach and non-parametric smoothing techniques.

To understand the price behaviour- model the volatility of stock price. Future price of stock is always uncertain, and it has to be described by a probability distribution, building up a model on this concept is a detailed description of how consecutive prices are determined.

LITERATURE REVIEW

There are several studies and articles which focuseson modelling the stock market volatility bycritically assessing the market of both developed anddeveloping countries. Among various models, many researcher have done analysis on the volatility of emerging stock markets using GARCH model to test its efficiency and accurateness.(Banumathy & Azhagaiah, 2015).

The studies related to modelling the volatility of stock market in Indian context are limited to the symmetric model of the market. To understand the feature of Indian stock market volatility, volatility model was estimated (Karmakar, 2005). The presence of leverage effect in Indian stock market has been analysed in this study which also highlighted that the estimation model GARCH(1,1) provided agoodestimate of market volatility forecasts. In another study of asymmetric volatility, it was observed that the conditional variance was asymmetric during the period of 14.5 years (from July 1990 to December 2004) (Karmakar, 2007). The study also identified that theEGARCH reveals a positive relation between risk and return and hence is an adequate model for the volatility estimation.

The estimation model GARCH(1,1) found out to be better model than the ARCH for explaining the volatility clustering and mean reverting in the series (Goudarzi & Ramanarayanan, 2010). The study analysed the Indian stock market volatility by takingBSE 500 stock index as the proxy for ten years. For the analysis, the ARCH and GARCH model were estimated. Further, the Akaike Information Criterion (AIC) and Schwarz Information

Criterion (SIC) was used for the selection of the best model.In another study of (Goudarzi & Ramanarayanan, 2011), BSE 500 stock index was selected for modelling the volatility of stock market. This study considers EGARH(1,1) and TGARCH(1,1) which are non-linear asymmetric model. As per the selection criteria, Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Log Likelihood Criteria (LL), TGARCH was found to be the best fit for modelling the volatility.
(Mittal, Arora, & Goyal, 2012) concluded that to capture symmetric and asymmetric effect, GARCH and PGARCH were found to be appropriate model by analysing the daily stock returns of 10 years (from 2000 to 2010).

(Wolfgang, Helmut, & Rong, 1997) explained the features of time series that can be analysed using nonparametric techniques. It is appropriate to have a general manner for the characteristics of interest that is measured more accurately when the sample size goes to infinity. Nonparametric methods have been reviewed to estimate spectral density, conditional mean, higher order conditional moments or conditional densities. The study also describes the estimation of density with correlated data, time series bootstrap methods, and nonparametric trend analysis.

There are various parametric models designed by (Abberger, 1997), in his study, to analyse volatility of financial market which are time series. These parametric methods require a known conditional distribution for the estimation of maximum likelihood. The analysis explains the conditional distribution of daily DAX returns by applying nonparametric methods. Kernel estimators are used for conditional quantiles which is derived from a kernel estimation of conditional distributions.

For the stock market evaluation of Indian stock market, TARCH and PARCH model results in better forecast volatility where BSE and NSE returns was considered for the analysis. ARMA(1, 1), ARCH(5), and EGARCH were found to be appropriate model for the foreign exchange market (Vijayalakshmi & Gaur, 2013). The study period was from 2000 to 2013. Some Indian studies attempting to model volatility found that for capturing the symmetric effect, GARCH(1,1) was the best model. EGARCH and PGARCH models were found to be acceptable for leverage effects. The selection of the best suited and appropriate model, however, depends on the model included in the analysis for evaluation.

The present study therefore used different GARCH family models and non-parametric methods in both symmetric and asymmetric effects to capture the return facts and to study the most suitable model in the volatility estimate.

TERMINOLOGY

Return is defined as a time series of asset prices display a growing tendency in the long run. Occasionally, however, price series may switch from upward to downward movements and vice-versa in the short or middle run. For this reason, prices of the same asset sampled at different periods of time may exhibit unequal means. Since this feature greatly complicates statistical inference, it needs to be eliminated. A simple approach consists in transforming the prices into returns, which empirically display more stationary behaviour.

Let us consider a financial asset with price Pt at date t that produces no dividends. The return over the period (t, t+H) is defined as

r (t, t+H) = $\frac{P_{t+1}-P_t}{P_t}$

The return depends on time t and the horizon H. Very oftenstatistical analysts investigate returns at a fixed unitary horizon which in general display more regular patterns than the initial series of prices.

r (t, t+1)=$\frac{P_{t+1}-P_t}{P_t}$

In theoretical or econometric analysis, the above formula is often replaced by the following approximation: Let us suppose the unitary horizon and a series of low- value returns: We obtain:

$$\tilde{r}(t, t+1) = logP_{t+1} - logP$$

$\cong \frac{P_{t+1}-P_t}{P_t}$= r (t, t+1)

Estimating volatility: Considerσ_n as the volatility of a stock variable on the day 'n', as estimated at the end of day 'n-1'. The square of the volatility$\sigma_n{}^2$, on day 'n' is the variance rate. Suppose the value of the stock variable at the end of the day 'I' is S_i, the variable $u_i$is defined as the constantly compounded return during day 1 (between the end of day 'i-1' and the end of day 'i')

$$u_i = \frac{S_i}{S_{i-1}}$$

An unbiased estimation of the variance rate/ day, $\sigma_n{}^2$, using the most recent m observations on the $u_i$is

$\sigma_n{}^2 = \frac{1}{m-1}\sum_{i=1}^{m}(u_{n-i} - \overline{u})^2$ (1)

where,$\overline{u}$= $\frac{1}{m}\sum_{i=1}^{m} u_{n-i}$

For calculating VAR, the formula in equation (1) can be followed as,

1. u_i is defined as the percentage variation in stock variable between the end of day 'i-1' and the end of day 'i'so that

$u_i = \frac{S_i - S_{i-1}}{S_{i-1}}$ (2)

2. $\overline{u}$ is expected to be zero.

3. m-1 is substituted by m.

The above changes make a very minor modification to the variance estimations, but they allow us to simplify the formula for the variance rate to

$\sigma_n{}^2$=$\frac{1}{m}\sum_{i=1}^{m} u^2{}_{n-i}$(3)

Equation (3) gives equal weight to all u_i's. The objective is to estimate the present level of volatility, σ_n. It therefore makesmore sensible if we give more weight tothe recent data. Therefore, the model is

$\sigma_n{}^2 = \sum_{i=1}^{m} \alpha_i u^2{}_{n-i}$ (4)

The variable α_i is the quantity of weight specified to the observations'i ' days ago. The $'\alpha'$ values are positive. If we choose them so that $\alpha_i < \alpha_j$ when i >j, less weight is given to older observations. The weights must be equal to unity, so that

$\sum_{i=1}^{m} \alpha_i = 1$

An additionto the knowledge in equation (4) is to pretend that there is a long-run average variance rate and thatmust be given some weight. Then the model will be written as

$\sigma_n{}^2 = \gamma V_L + \sum_{i=1}^{m} \alpha_i u^2{}_{n-i}$ (5)

where, V_L is a long-run variance rate and γ is the weight assigned to V_L and $\gamma + \sum_{i=1}^{m} \alpha_i = 1$

is known as an ARCH (m) model

The estimation of the variance is biased on a long-run average variance and m observations.

THE GARCH (1, 1) MODEL:

GARCH (1, 1) model is proposed by Bollerslev in 1986 is an extended version of the ARCH model where the variance of the disturbance at time 't' influenced by on its own lag as well as the squared disturbances.

The difference between GARCH (1, 1) model and the Exponentially Weighted Moving Average (EWMA)Model is analogous to the difference between the equations (4) and (5). In GARCH (1, 1), $\sigma_t{}^2$ is calculated from a long-run average variance rate, V_L, as well as from σ_{t-1} and ε_{t-1}. The equation for the GARCH (1, 1) is

$\sigma_t{}^2 = \gamma V_L + \alpha_1 \varepsilon^2{}_{t-1} + \beta \sigma^2{}_{t-1}$ (6)

where, γ is the weight assigned to V_L, α_1 is the weight assigned to $\varepsilon^2{}_{t-1}$ and β is the weight assigned to $\sigma^2{}_{t-1}$. And more importantly, $\gamma + \alpha_1 + \beta = 1$

The "(1, 1)" in GARCH (1, 1) specifies that $\sigma_t{}^2$ is biased on the most recent observation of $\varepsilon_t{}^2$ and most recent estimation of the variance rate. Setting $\alpha_0 = \gamma V_L$, the GARCH (1, 1) model can also be written as:

$\sigma_t{}^2 = \alpha_0 + \alpha_1 \sum_{i=1}^{p} \varepsilon^2{}_{t-1} + \beta \sigma^2{}_{t-1}$ (7)

This model is generally used for estimating the parameters. After estimating α_1 and β , we can calculate α_0 as 1- α_1 - β. The long-run variance $V_L = \frac{\alpha_0}{\gamma}$. For GARCH (1, 1) process, the sum $\alpha_1 + \beta < 1$, else the weight to the long-run variance is considered to be negative.The parameters of GARCH can be estimated using maximum likelihood estimator.

NON PARAMETRIC REGRESSION:

Non-parametric regression is a set of techniques used to estimate the regression curve without making strong assumptions about the shape of the true regression function. The non-parametric techniques are useful for model building and checking parametric form and for data description. The non-parametric model is of the form $y = m(x) + \varepsilon$
And for the i^{th} observation $y_i = m(x_i) + \varepsilon i=1,2\ldots\ldots\ldots n$
where, *y* is the response variable and*m (x)* is the mean response of the regression function.

The nonparametric method of estimating a regression curve has the following advantages:

1. It offers a useful method of discovering a general rapport between two or more variables.
2. It provides prediction of observation yet to be given without referring to a stable parametric model.
3. It provides a technique for finding outliers by studying the effect of remote points.
4. Nonparametric regression creates an easy method of replacing for missing values or interpolating between adjacent x values.

Regression smoothing techniques are specially used to estimate the regression function in non-parametric methods. A regression smoother is a techniqueofbriefing the trend of a responsemeasurement '*y*' as a function of one or more predictor measurements *x*. Smoothing is a kind of averaging the observations around the target value of the predictor variable. The averaging is carried out in the neighbourhood around the target value '*x'*. The smoothing techniques differ mainly in their method of averaging the values. The main and important decision to be made in any of the smoothing techniques is to fix the size of the neighbourhood. In this study, for the smoothing analysis we have used Nadaraya Watson Estimator i.e. at some point *x*,

$$\widehat{m}\ (x) = \sum_{i=1}^{n} y_i\, K_h\ (x - x_i) / \sum_{i=1}^{n} K_h\ (x - x_i)$$

SMOOTHING RESIDUALS

For a parametric model $S\Theta$which could be either linear on nonlinear in unknown parameter, we wish to test the hypothesis that

$$H_0: m \in S\Theta = \{m(.;\ \theta): \theta \in \Theta\} \qquad (8)$$

Let $\hat{\theta}$ be consistent estimate of θ under H_0 .Define the residual $e_1, e_2, e_3, \ldots\ldots e_n$, as

$$e_i = Y_i - m(x_i, \widehat{\theta}), \qquad i = 1,2, \ldots\ldots n \qquad (9)$$

If H_0 is true, then these residuals should behave more or less like a batch of zero mean uncorrelated random variable. Hence when the H_0 is true, a linear smooth $\hat{g}$ will tend to be relatively flat and cantered about zero. Plot $\hat{g}(.;s)$ and see how much it differs from zero function. A test statistic that more objectively measure the discrepancy of $\hat{g}(x;s)$ from zero function is given below.

The statistic used to test H_0 is of the form $T = \frac{\| g(.;S)\|^2}{\hat{\sigma}^2}$ (10)

where, the $\|g(.;s)\|$ is quantity that measure the size of the function 'g' and $\hat{\sigma}^2$ is model free estimator of error variance σ^2. The commonly used estimates of σ^2 based on pseudo residuals e_{1i} and, e_{2i}, $i = 1,2,\ldots\ldots.n$ are

$$\widehat{\sigma_d^2} = \frac{1}{2(n-1)}\sum_{i=1}^{n} e_{1i}^2$$

where, $e_{1i} = Y_i - Y_{i-1}$ $i = 2,3,\ldots\ldots..,n-1$, (11)

and $\widehat{\sigma_e^2} = \frac{1}{n-2}\sum_{i=2}^{n-1}\frac{e_{2i}^2}{(1+a_i^2+b_i^2)}$ (12)

where, $e_{2i} = \frac{X_{i-1}-X_i}{X_{i+1}-X_{i-1}}Y_{i-1} + \frac{X_i-X_{i-1}}{X_{i+1}-X_{i-1}}Y_{i+1} - Y_t$ (13)

$=a_iY_{i-1} + b_iY_{i+1} - Y_t$, $i = 2,3,\ldots\ldots\ldots\ldots n-1$

where, a_i and b_i are the coefficients of Y_{i-1} and Y_{i+1}.

EMPIRICAL APPLICATION

The objective of this study is to determine a volatility model for the return series using non-parametric regression. The GARCH model and non-parametric regression models are used to develop appropriate model and the same is used for the study. In recent years nonparametric methods of curve estimation are used to develop appropriate model for the phenomenon under study. It is a data driven approach and provides information regarding the key features in the data. We have explored the use of non-parametric smoothing techniques for the empirical study.

In this context appropriate MATLAB programs are developed to implement the steps involved in the GARCH model approach and non-parametric regression approach. The two approaches are compared to obtain the best fit.

Stock Market daily data of Cipla Ltd for the year of one year starting from 1st Jan 2018 to 13th March 2019 have been used (particularly this year is selected because of price fluctuations in the stock market) as a variable for the study. The data has been tested using GARCH and Non-Parametric smoothing techniques. The problem of testing ARCH and GARCH effect and fitting the model is considered. In nonparametric smoothing method, the problem of estimation of non-parametric smoothing curve is carried out. To see the appropriateness comparing the residual sum of square with the existing model, testing the goodness of fit for the model have been used for the study.

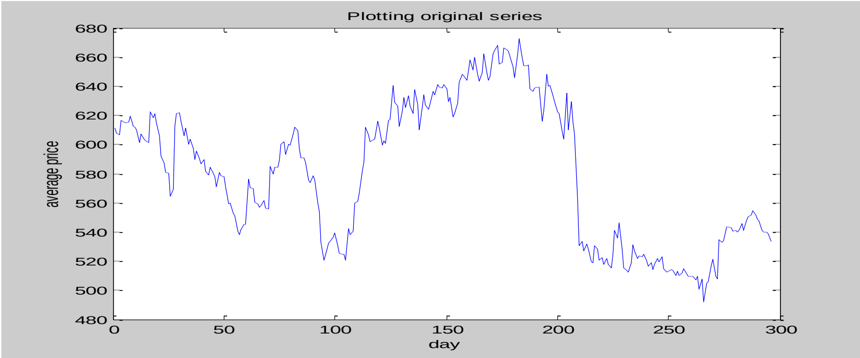


Figure 1. Plotting original return series

The graph shows that there is trend component in the time series data. This indicates that the series is non stationary. As evidence we plot the ACF curve to support the claim.

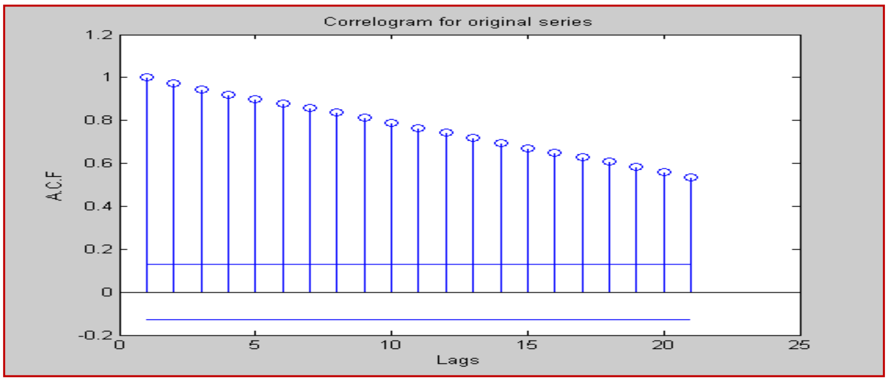


Figure 2. Plotting Correlogram for original return series

Here all autocorrelation curves lie outside the 2σ limits. Autocorrelations for the original series shows that the series is non stationary. Non stationary is removed by differencing the series twice. Correlogram for the differenced series is given below where most of the spikes are within 2σ limits, which signifies that the differenced series is stationary.

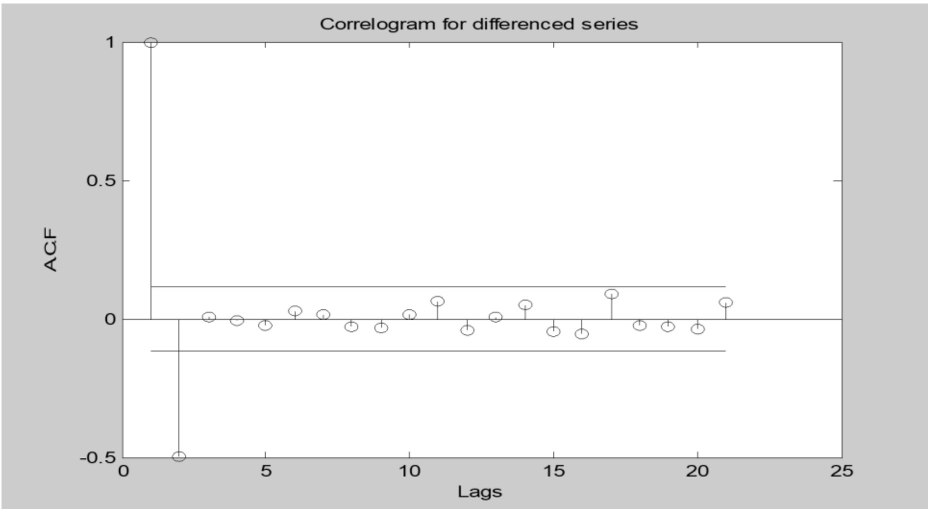


Figure 3. Plotting Correlogram for differenced return series

Empirical evaluation of ARCH and GARCH models:

Since GARCH is Generalized ARCH, existence ARCH implies the existence of GARCH effect. If H_0 is rejected then using GARCH model is justified, else GARCH model cannot be used. If null hypothesis is rejected it implies the existence of the GARCH effect. Therefore, the presence of GARCH effect is tested by defining the hypothesis,

H_0: No ARCH effect exists.

H_1: ARCH effect exists.

Special features of financial time series

i) Absence of auto correlation in the return series.

ii) Squared returns exhibit significant serial correlation.

iii) The return series follow heavy-tailed distribution.

Table 1*:* Representing Summary of stock price

Statistic	Value
Minimum	492.1
Maximum	672.8
Mean	581.1
Skewness	0,0093
Kurtosis	1.6799

Table 2*:* Representing Summary of log return series

Statistic	Value
Minimum	-0.0753
Maximum	0.0735
Mean	-0.0005
Skewness	0.3939
Kurtosis	3.8006

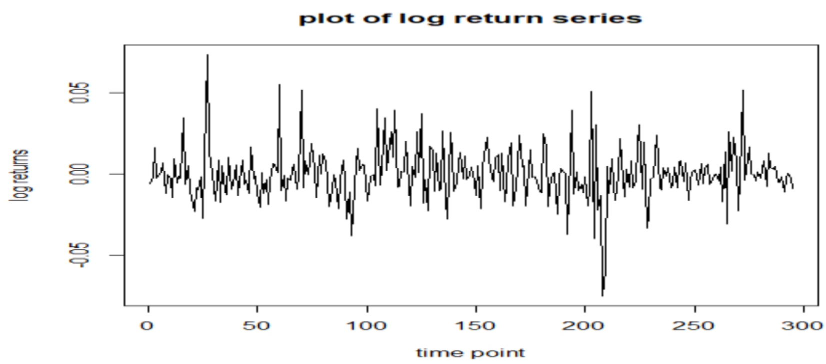


Figure 4. Plotting log return series

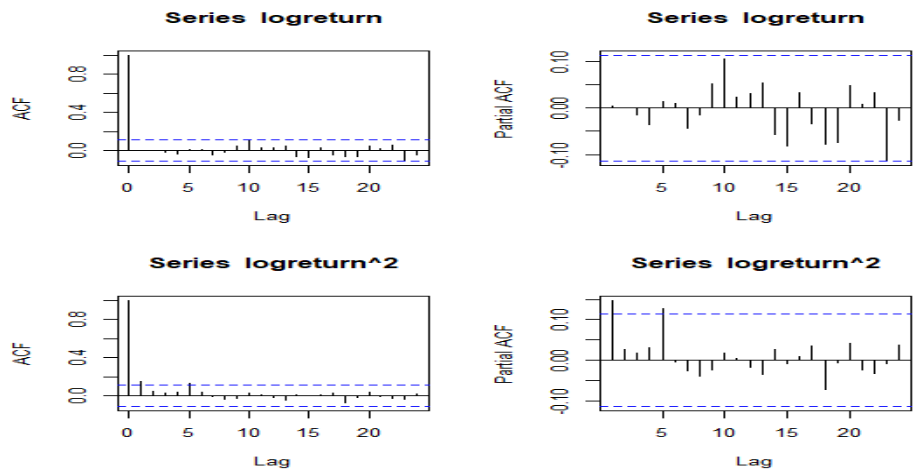


Figure5 . Plotting ACF

Observation:

We can see that all the spikes in the ACF plot of log returns falls within the confidence interval. It confirms the absence of the autocorrelation in the log return series. Further, some spikes in the squared log return series are outside the confidence limit which confirms the serial correlation between squared log returns. The computed value of kurtosis for log return series is 3.8006 (>3). Thus, the feature of financial time series is satisfied by the data under study. To proceed to fit ARCH/GARCH model we require the order of the process. From the ACF and PACF plots of squared return we can observe the one spike is outside the confidence limit (Note: **Count the number of first significant spikes outside the 3-sigma limit, and in ACF the first spike is always outside because autocorrelation at lag zero is always=1**). Thus GARCH(1,1) model may be a good guess to start.

The functions used, the inputs taken, and the output obtained are given below:

1. GARCHFIT: This function is used to fit the GARCH model. The input used is return series and the outputs obtained are the estimates of the coefficients of the GARCH model, standard error of the coefficients, least square fit value innovations and sigma.

2. ARCH test: This function is used to test the existence of ARCH effect. The inputs taken here are the residual obtained from the GARCH fit, the vector of lags of the squared residuals included in the ARCH test statistic, the level of significance of the hypothesis test is 5%.

Table 3: Representing output values for Ljung Box Test in original return series

Model	Boolean Value	P-Value	Test Statistic	Critical Value
ARCH	1	0.0014	58.5620	3.8415
GARCH	1	0	59.0343	31.4104

1. The Boolean values, in which ‘1’ indicates the rejection of null hypothesis and ‘0’ indicates the acceptance of the null hypothesis

2. ARCH test statistic value, both the computed and the critical value of the chi-square distribution.

Table 4*:* Representing Fit Summary

	Estimate	Std. Error	t-Value	Pr(>$\|t\|$)
Mu	1.960e-04	9.057e-04	0.216	0.8286
Omega	5.536e-05	2.921e-05	1.895	0.0581
Alpha 1	9.988e-02	4.800e-02	2.081	0.0374 *
Beta 1	6.923e-01	1.289e-01	5.371	7.83e-08 ***

3. The estimated co-efficient of GARCH model are α = 0.0998 and β =0.6923. Since α+β<1, the GARCH (1,1) is stationary with finite variance.

To examine the suitability of ARCH model, ARCH test was carried out which gave Boolean value 1 with p-value 0.0014. Therefore, the null hypothesis is rejected which indicates that there exists ARCH effect.
To examine the suitability of GARCH model, Ljung Box test was carried out which gave the Boolean value 1 with p-value 0. Therefore, the null hypothesis is rejected which indicates the existence of GARCH effect.
Table 5*:* Representing Residual Analysis

			Statistic	P- Value
Jarque-Bera Test	R	Chi^2	171.2063	0
Shapiro-Wilk Test	R	W	0.9392	1.179569e-09
Ljung-Box Test	R	Q(10)	7.1107	0.7149
Ljung-Box Test	R	Q(15)	11.0814	0.7468
Ljung-Box Test	R	Q(20)	15.9181	0.7217
Ljung-Box Test	R^2	Q(10)	5.9687	0.8179
Ljung-Box Test	R^2	Q(15)	7.6402	0.9374
Ljung-Box Test	R^2	Q(20)	9.8324	0.9711
LM Arch Test	R	TR^2	6.1212	0.9098

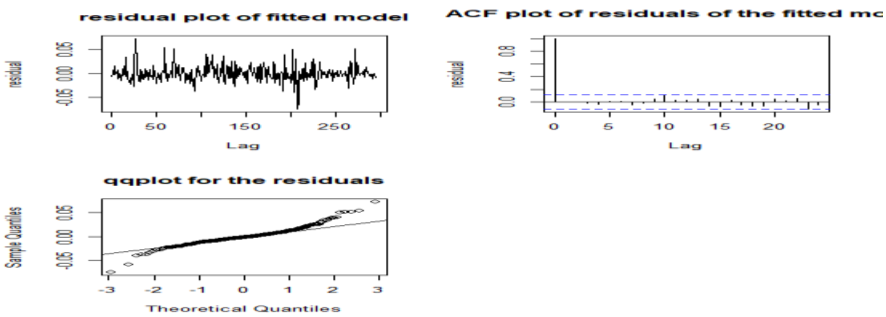


*Figure 6.*Plotting Residuals of the fitted model

Observation:

Here the residuals are uncorrelated. There is no ARCH effect left in the residual series (LM test p-value:0.9098>0.05, accept the null hypothesis H1: No ARCH effect). Also, qq plot shows that residuals not follow normal distribution (Not a strong assumption). The mean of residual is -0.0006 and variance is 0.0002. Thus, we can say that residuals follow a white noise process (iid random variables with zero mean and constant variance and are uncorrelated).

So the fitted model for Cipla Ltd for the period from 01 January 2018 to 13 March 2019 is $\boldsymbol{y_t = \sigma_t \varepsilon_t}$, $\boldsymbol{\sigma_t^2 = 0.0998 y_{t-1}^2 + 0.6923 \sigma_{t-1}^2}$

Empirical evaluation of the data using graphs:

Fig 6: Plotting original return series and estimated values from GARCH fit

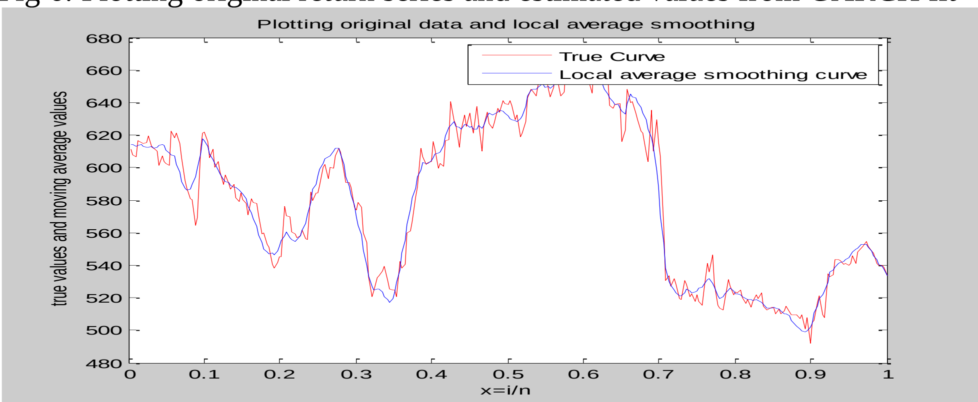
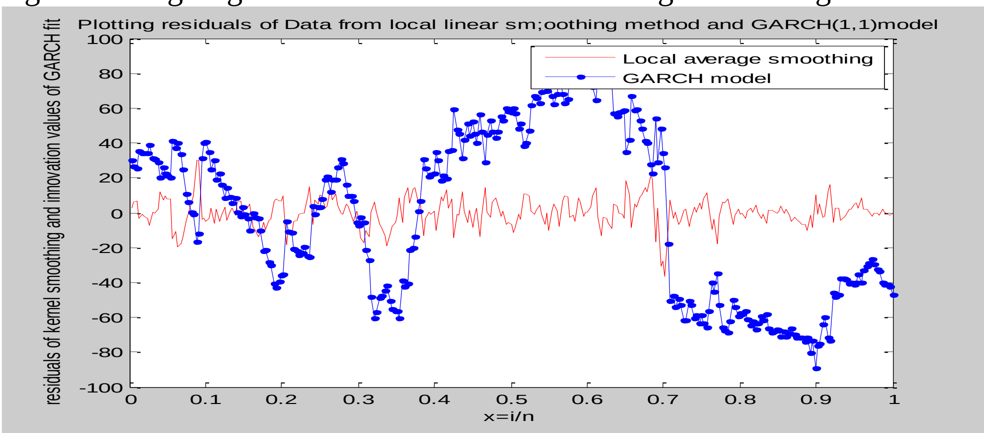


Fig 7: Plotting original return series and local average smoothing values



. Fig 8: Plotting residuals from local average smoothing and GARCH model

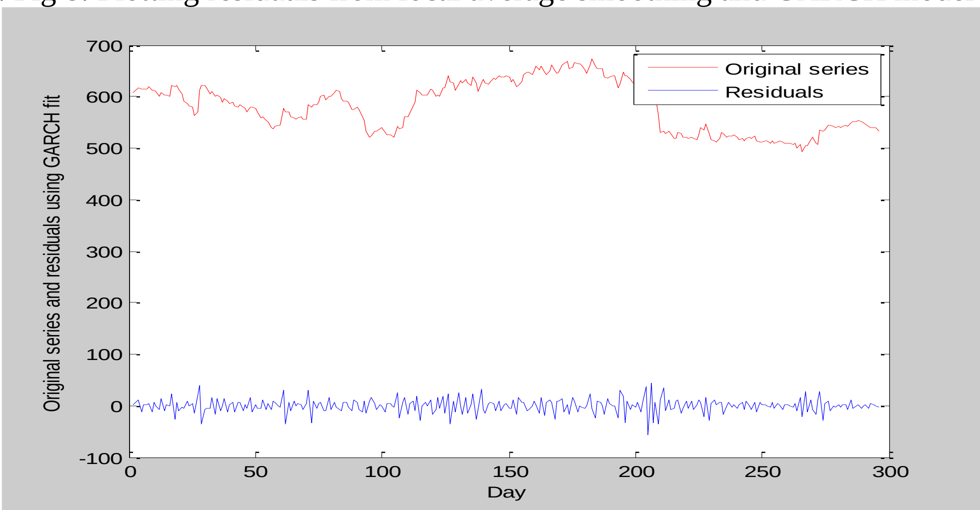


Fig 9: Plotting original return series and the residuals

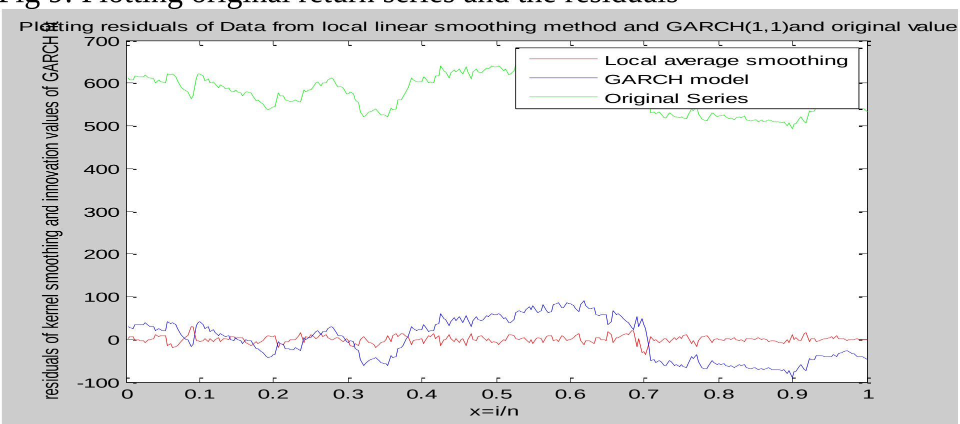


Fig 10: Plotting residuals from local average smoothing, GARCH model and original return series

To examine the appropriateness of the estimated curve, lack of fit test is considered, and the test statistic obtained is T=0.598290<1. This implies that the non-parametric model is considerably good fit for the data.

Values of Residuals sum of squares of parametric and non-parametric techniques

Model	Residual sum of Squares
GARCH	53256.99
Kernel Estimator	20789.70

By comparing the residual sum of squares, the computed results show that non parametric smoothing approach gives less residual sum of squares compared to GARCH, therefore nonparametric smoothing approach is a better fit compared to GARCH model for financial data.

CONCLUSION

1. The same techniques and test procedures are applied for other listed companies in the Indian Stock Market. An approach was proposed for the testing of volatility using non parametric regression method. Model for volatility was estimated using Kernel Smoothing and compared it with the GARCH model.
2. To examine the suitability of ARCH model, ARCH test was carried out which gave Boolean value 1 with p-value 0.0014. Therefore,we reject the null hypothesis and conclude that there exists ARCH effect.
3. It is observed that in most of the cases Non Parametric model is a good fit for financial data when compared with the existing GARCH model.
4. To verify the appropriateness, the models can be applied for the generated return series using simulation procedure.

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