STUDY OF VOLATILITY IN THE STOCK MARKET

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Abstract: In today'sera, most of people are interested in investing some part of their income in stock market to get a good return. Share investment is one of the popular ways of investing money, which gives better returns. But there is risk in investment of capital in share market. So our aim is to study how to minimize this risk.Stock price forecasting is a popular and important topic in financial studies .Time series analysis is the most common method used to perform this task. The main objective of this paper is to study the trend of share prices for Nestle Company and also predicting the future values. Analysis is done by using time series analysis. For the statistical analysis MS-Excel, MINITAB, R-software is used.Data consists of daily opening prices for Nestle Company shares, the period considered here is from 1st January 2004 to 31st December 2013.The Conclusions of this paper is that time series plot of nestle company is volatile in nature and forecasting values goes on decrease from high price to low price.

Keywords: Volatility, ARIMA model, ARCH model, Forecasting.

1. INTRODUCTION

Volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means a security's value can potentially be spread out over a larger range of values whereas, lower volatility means a security's value does not fluctuate , but changes in value over a period of time.Stock market investment is good way to invest money which gives most of the time good returns. Investment per share is nothing but the combination of market price, premium and brokerage on face value. People are always interested to invest their money where they get profit.

Nestle India's first production facility, set up in 1961 at Moga (Punjab), was followed soon after by its second plant, set up at Choladi (Tamil Nadu)in 1967.The 4 branch offices in the country help facilitate the sales and marketing of its products .They are in the Delhi, Mumbai, Chennai and Kolkata. The Nestle India head office is located in Gurgoan, Haryana. The CEO of Nestle Company is Paul Buckle.Following are the list of some products manufactured by a company.Nestlemilkmaid, Nestlemunch , Nescafe sunrise, Ice cream , Syrups , Honey, Candies, Maggie sauces, Magi pichkoo, Nestle fresh and natural dahi, Nestle Kitkat.

As per the market –wise position Nestle India stands first in instant noodles & ketchups, second in healthy soups, No.1 in instant coffee & No.2 in overall chocolate category.

2. OBJECTIVES

I. To observe original series and identify time series components then estimate and eliminate it.
II. To check volatility in the time series plot of shares ofcompany.

3. Research Methodology

We collected secondary data of price of Nestle Company shares from 2000 to 2013. For the period 2004 to 2013 this share was not split, so we consider this period for study. The collected data consists of Date, Opening price of share, and closing price of share, Volume of share, maximum price of day, and minimum price of day. We concentrate our study at daily opening prices of a share.

The data we used in this analysis is taken from www.yahoo.finance.com.For Statistical analysis we have used MINITAB, R-software.

4. STATISTICAL ANALYSIS:

Following is the time series plot of opening values in the Stock market of a company.

Fig.1 Time Series Plot

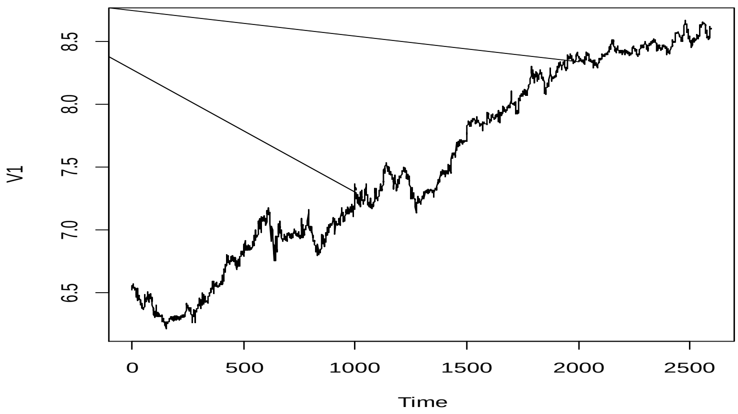


Fig.2 Acf plot of open series

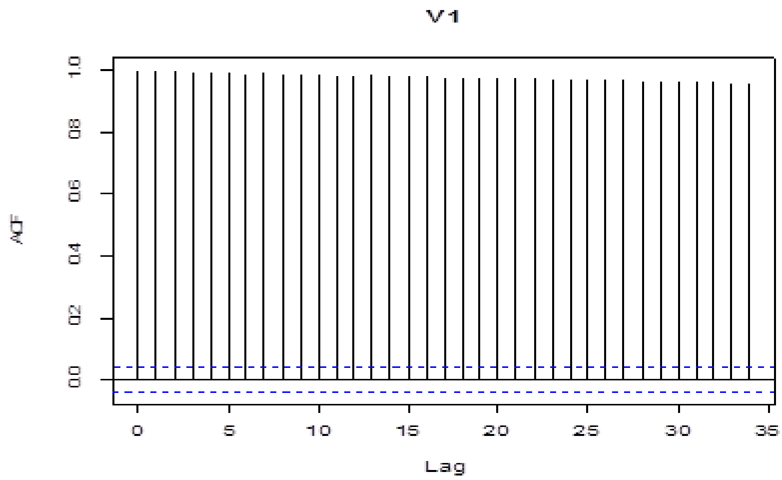


Fig.3PACF Plot of openseries

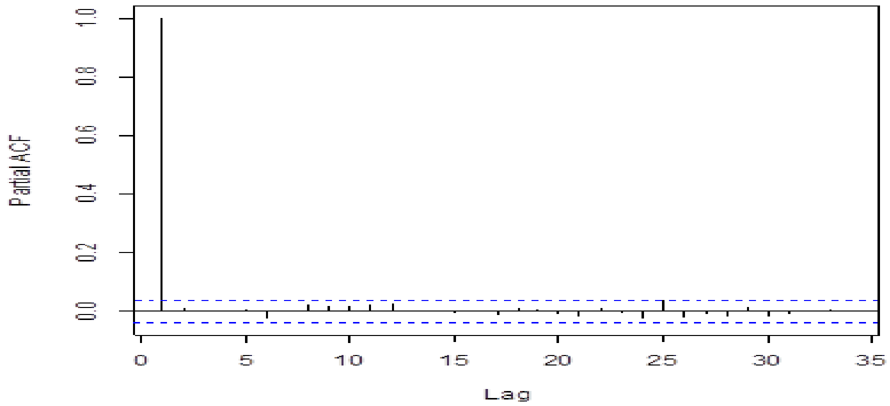
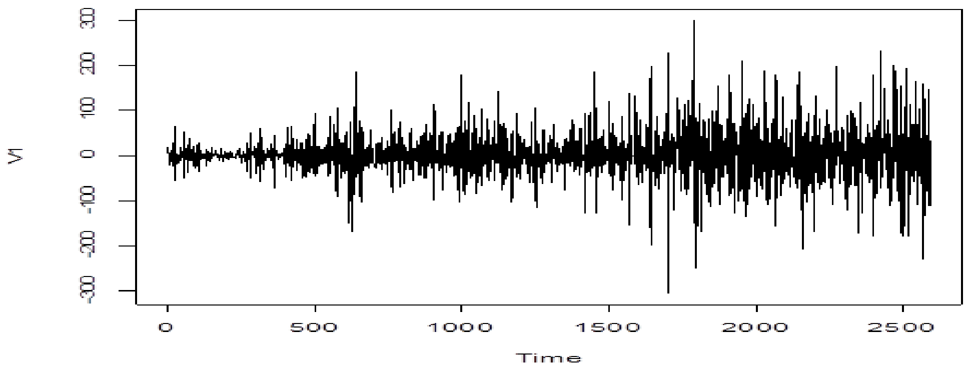


Fig.4Differenced Time series plot

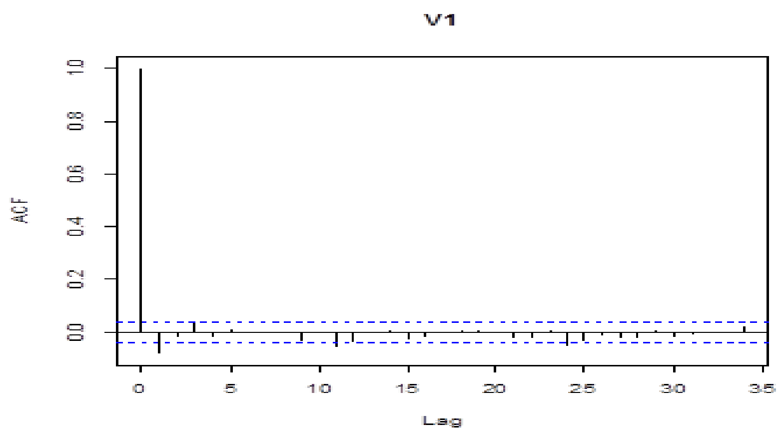


acf (openseriesdiff1, lag.max=20, plot=FALSE)

Table 1:Autocorrelations of series 'openseriesdiff 1'by lag

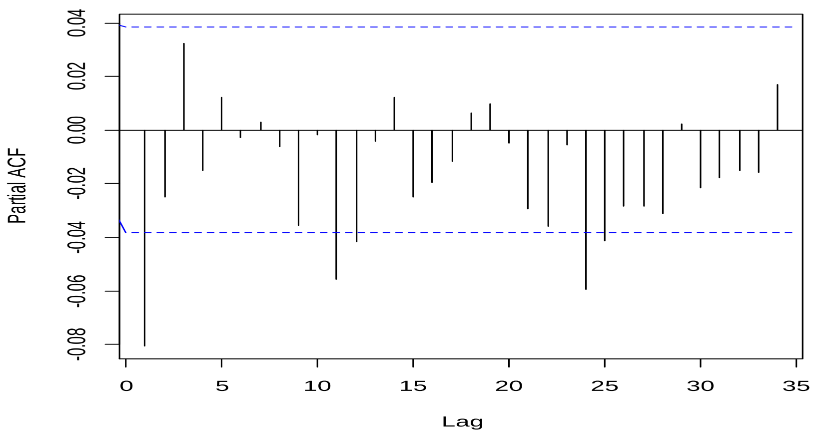
0	1	2	3	4	5	6	7	8	9	10
1.0	-0.081	-0.018	0.036	-0.020	0.013	-0.003	0.002	-0.005	-0.035	0.005
11	12	13	14	15	16	17	18	19	20	
2.0	0.055	-0.035	0.006	0.009	-0.027	-0.016	-0.007	0.008	0.010	

Fig.5 Differenced PACF Plot



Partial autocorrelations of series 'openseriesdiff1', by lag

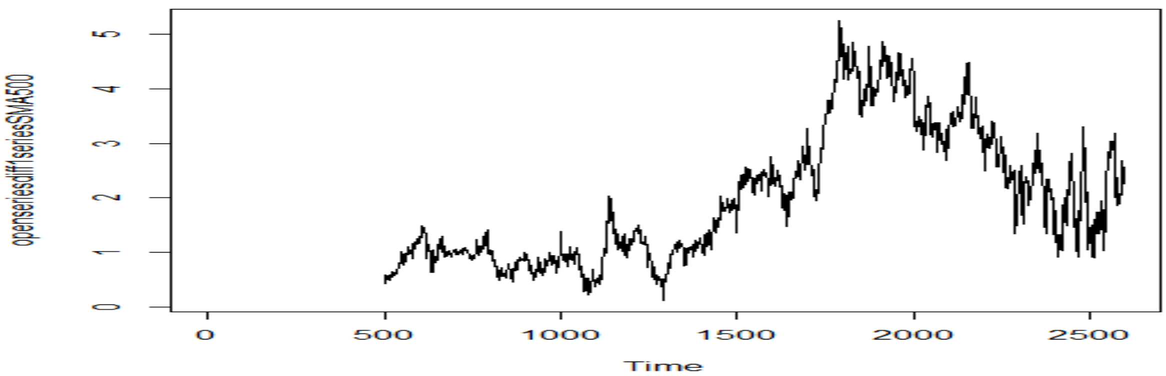
Fig.6 Series open series difference 1



From the above Acf and Pacf plot the data is in stationary& we can find order of the transformed data.

To estimate the trend component more accurately, we might want to try smoothing the data with a simple moving average of a higher order.

Fig.7 Holt winter without seasonality



The data smoothed with a simple moving average of order 500 days gives a clearer picture of the trend component.

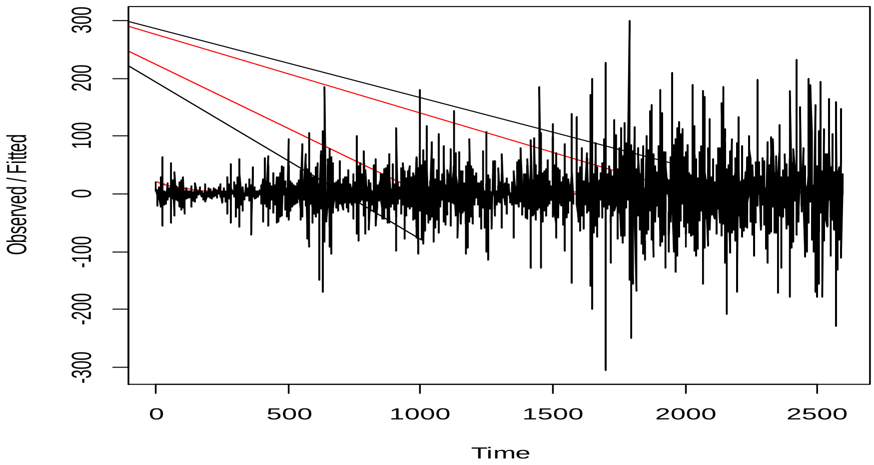
Forecasting of open series differences:-Holt winter without seasonality.

openseriesdiff1forecasts <- HoltWinters (openseriesdiff1, alpha=FALSE, beta=FALSE)

Holt-Winters exponential smoothing without trend and without seasonal component.

The output of HoltWinters () tells us that the estimated value of the alpha parameter is about 0.006957, this is very close to zero, telling us that the forecasts are based on both recent and less recent observations (although somewhat more weight is placed on recent observations).

Fig.8 Holt-Winters filtering



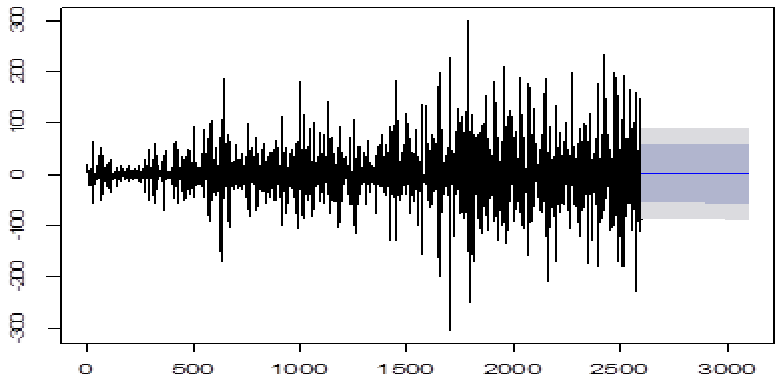
We can see from the plot that there is more constant level. The random fluctuations in the time series seem to be more constant in size over time, thus, we can make forecasts using simple exponential smoothing.

Table 2 Forecasts by using simple exponential smoothing

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2597	2.163703	-56.06915	60.39655	-86.89575	91.22316
2598	2.163703	-56.07056	60.39796	-86.89791	91.22532
2599	2.163703	-56.07196	60.39937	-86.90007	91.22747
2600	2.163703	-56.07337	60.40078	-86.90222	91.22963
2601	2.163703	-56.07478	60.40219	-86.90438	91.23178
2602	2.163703	-56.07619	60.40360	-86.90653	91.23394
2603	2.163703	-56.07760	60.40501	-86.90869	91.23609
2604	2.163703	-56.07901	60.40642	-86.91084	91.23825
2605	2.163703	-56.08042	60.40783	-86.91300	91.24040
2606	2.163703	-56.08183	60.40924	-86.91515	91.24256
2607	2.163703	-56.08324	60.41064	-86.91731	91.24471
2608	2.163703	-56.08465	60.41205	-86.91946	91.24687
2609	2.163703	-56.08606	60.41346	-86.92162	91.24902
2610	2.163703	-56.08746	60.41487	-86.92377	91.25118

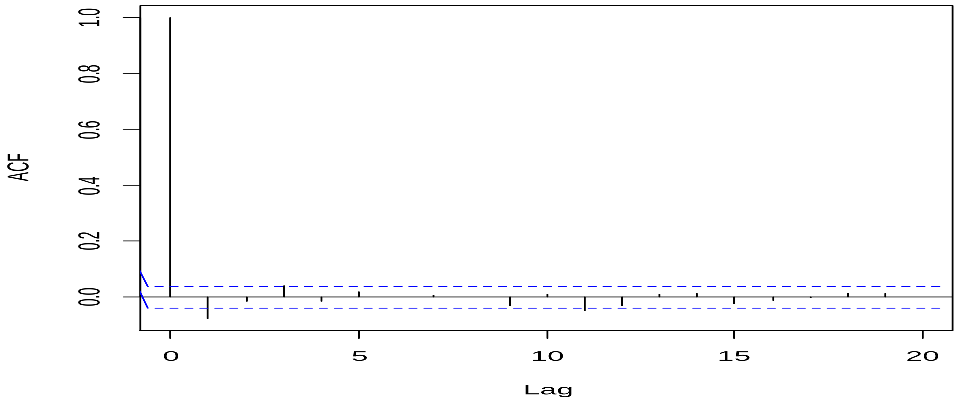
The forecast. HoltWinters() function gives you the forecast for a daily data, a 80% prediction interval for the forecast, And a 95% prediction interval for the forecast. For example, the forecasted open price for 2610 is about 2.163703 Rs With a 95% prediction interval of (-86.92377, 91.25118).

Fig.9 Forecasts from Holt-Winters



Here the forecasts for 2596-3096 are plotted as a dark blue line, the 80% prediction interval as an dark grey shaded area, and the 95% prediction interval as a light Grey shaded area.
If the predictive model cannot be improved upon, there should be no correlations between
Forecasterrors (SSE) for successive predictions. In other words, if there are correlations between forecast errors for
Successive predictions, it is likely that the simple exponential smoothing forecasts could be improved upon by
another forecasting technique.Tofigure out whether this is the case, we can obtain a correlogram of the in-sample forecast errors for lags 1-20.

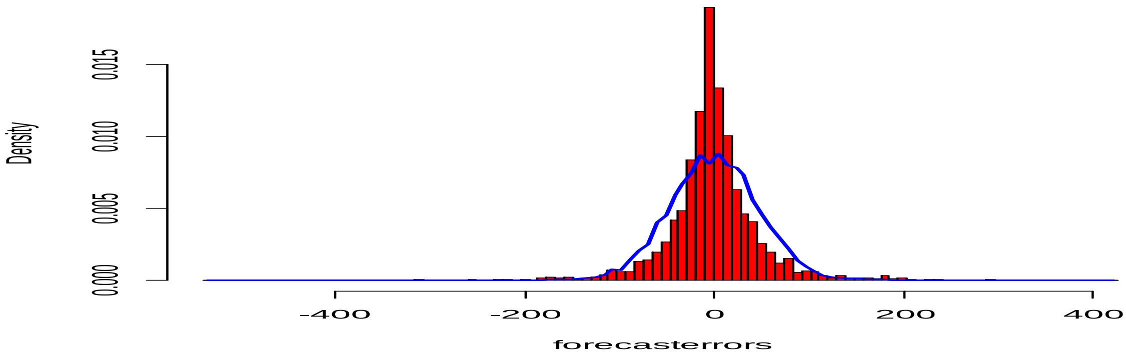
Fig.10 Correlogram



- We can see from the sample correlogram that the autocorrelation at lag1, 3 is just touching the significance bounds.
To test whether there is significant evidence for non-zero correlations at lags 1-20, we can carry out a Ljung-Box test.

- Here the Ljung-Box test statistic is 36.015, and the p-value is 0.01532, so there is little evidence of non-zero autocorrelationsin the in-sample forecast errors at lags 1-20.
To be sure that the predictive model cannot be improved upon, it is also a good idea to check whether the forecasterrors are normally distributed with mean zero and constant variance. To check whether the forecast errors haveConstant variance, we can make a time plot of the in-sample forecast errors. PlotForecastErrors (openseriesdiff1forecasts2$residuals)

Fig.11 Histogram of Forecast errors



>mean(openseriesdiff1forecasts$residuals)
[1] 0.9879903

- The plot shows that the distribution of forecast errors is roughly centred on zero, and is more or less normally distributed, although it seems to be slightly skewed to the right compared to a normal curve. However, the rightskew is relatively small, and so it is plausible that the forecast errors are normally distributed with mean zero.TheLjung-Box test showed that there is little evidence of non-zero autocorrelations in the in-sample forecasterrors, and the distribution of forecast errors seems to be normally distributed with mean zero. This suggeststhat the simple exponential smoothing method provides an adequate predictive model for open prices, whichprobably cannot be improved upon. Furthermore, the assumptions that the 80% and

95% predictions intervalswere based upon (that there are no autocorrelations in the forecast errors, and the forecast errors are normallydistributed with mean zero and constant variance) are probably valid.

- Exponential smoothing methods do not make any assumptions about correlations between successive valuesof the time series, in some cases we can make a better predictive model by taking correlations in the data into account. Autoregressive Integrated Moving Average (ARIMA) models include an explicit statistical model **for** the irregular component of a time series that allows for non-zero autocorrelations in the irregular componentARIMA models are defined for stationary time series.We have an ARIMA (p, d, q) model, where d is the orderof differencing used.

ARMA model(3,2)

openseriesdiff1arima <- arima(openseriesdiff1, order=c(3,0,2))

Series: openseriesdiff1

ARIMA (3, 0, 2) with non-zero mean Coefficients:

Table 3

Model	ar1	ar2	ar3	ma1	ma2	Intercept
Coefficients	-0.1886	0.1876	0.0484	0.1073	-0.2204	1.7957
Standard error	0.7167	0.5443	0.0545	0.7171	0.4985	0.8219

sigma^2 estimated as 2023: log likelihood=-13558.9

AIC=27131.8 AICc=27131.85 BIC=27172.83

ARIMA(3,1,2):-

openseriesdiff1arima <- arima (openseriesdiff1, order=c(3,1,2))

Series: openseriesdiff1

ARIMA (3,1,2)

Coefficients:

Table 4

	ar1	ar2	ar3	ma1	ma2
Coefficients	-0.3939	-0.0476	0.0273	-0.6870	-0.3130
Standard error	0.4912	0.0454	0.0239	0.4915	0.4915

Sigma^2 estimated as 2023: log likelihood=-13558.21

AIC=27128.41 AICc=27128.44 BIC=27163.58

Forecast of ARIMA(3,1,2)

> openseriesdiff1forecasts <- forecast.Arima (openseriesdiff1arima, h=500)

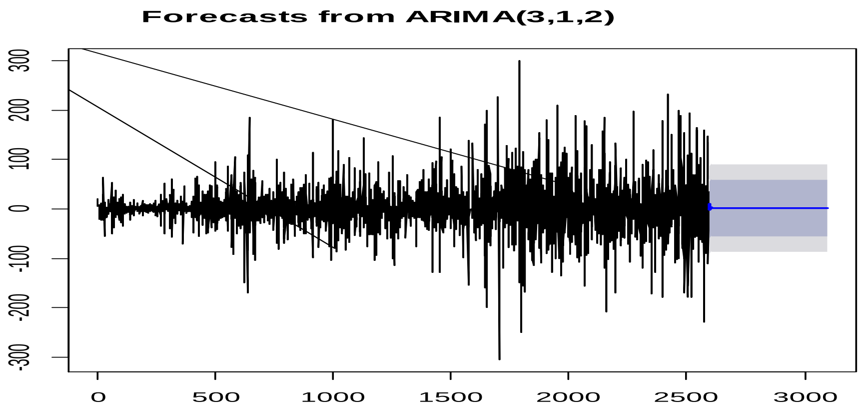
Table 5

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2597	9.948906	-47.70947	67.60729	-78.23198	98.12979
2598	2.936885	-54.90804	60.78181	-85.52929	91.40306
2599	-1.550140	-59.40184	56.30156	-90.02668	86.92640
2600	3.292410	-54.60006	61.18488	-85.24649	91.83131
2601	1.406984	-56.49265	59.30662	-87.14287	89.95684
2602	1.796816	-56.10341	59.69704	-86.75393	90.34756
2603	1.865124	-56.03510	59.76535	-86.68563	90.41588
2604	1.768212	-56.13201	59.66844	-86.78254	90.31896
2605	1.813776	-56.08646	59.71401	-86.73699	90.36455
2606	1.802303	-56.09793	59.70254	-86.74846	90.35307
2607	1.802010	-56.09822	59.70224	-86.74876	90.35278
2608	1.803915	-56.09632	59.70415	-86.74685	90.35468
2609	1.802865	-56.09737	59.70310	-86.74790	90.35363
2610	1.803180	-56.09705	59.70342	-86.74759	90.35395

The original time series for the Nestle company includes the daily open prices for 2596 days(2004-2013). The forecast.Arima ()function gives us a forecast of the open prices for next 500 days (2597-3096), as well as 80% and 95% prediction intervals for those predictions.

plot.forecast(openseriesdiff1forecasts)

Fig.12 Forecasts from ARIM (3, 1, 2)



From timeseries plot there is volatility (original open differncing plot)

We go for ARCH(q)model:-

openseriesdiff1.arch <- garch(openseriesdiff1, order = c(0,2)) # Fit ARCH(2)

Table 6

I	INITIAL X(I)	D(I)
1	1.836603e+03	1.000e+00
2	5.000000e-02	1.000e+00
3	5.000000e-02	1.000e+00

summary(openseriesdiff1.arch)

Call:

Garch(x = openseriesdiff1, order = c(0, 2))

Model:

GARCH(0,2)

Residuals:

Table 7

Min	1Q	Median	3Q	Max
-5.917849	-0.405536	0.001756	0.467616	7.941094

Coefficient(s):

Table 8

	Estimate	Std. Error	t value	Pr(>|t|)
a0	800.41390	17.67027	45.30	<2e-16 ***
a1	0.54818	0.03000	18.27	<2e-16 ***
a2	0.33459	0.02198	15.22	<2e-16 ***

Signif.codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Diagnostic Tests: JarqueBera Test

data: Residuals

X-squared = 4675.834, df = 2, p-value < 2.2e-1

Box-Ljung test

data: Squared.Residuals

X-squared = 1.0662, df = 1, p-value = 0.3018

Fig.13 Histogram of open series difference 1

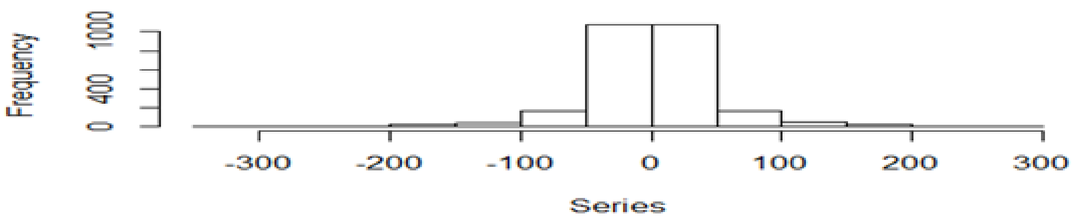


Fig.14 Histogram of Residuals

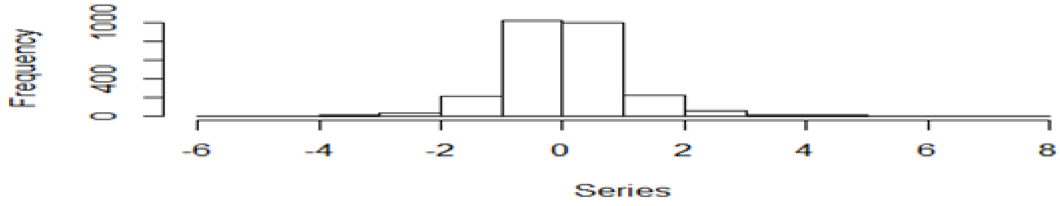


Fig.15 Q-Q Plot of open series difference 1

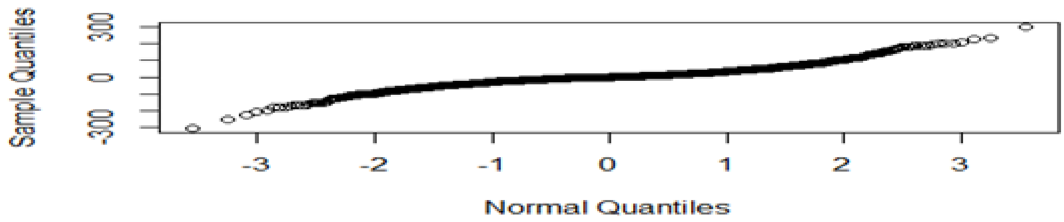


Fig.15 Q-Q Plot of Residuals

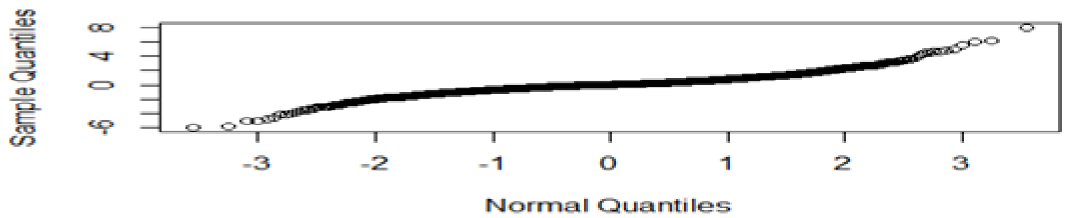


Fig.16 ACF of Squared open series diff 1

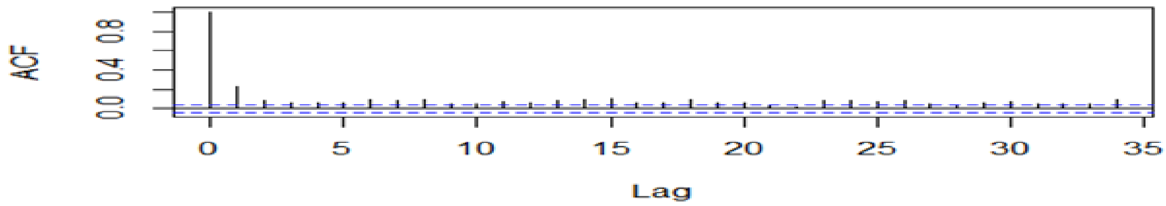
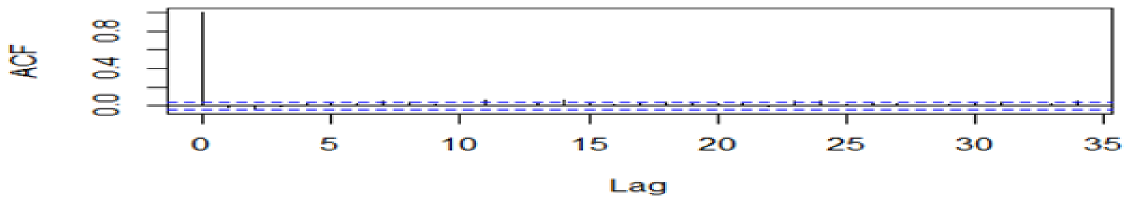


Fig.17 ACF of Squared Residuals



5. CONCLUSIONS:

Seasonal variation in the daily opening prices of are in increasing trend(From Fig 1). From Acf and Pacf plots (Fig.2 and Fig.3) the data is non stationary. Time series plot shows data is non seasonal(From Fig.4). From Differenced Acf and Pacf plots (Fig.5 and Fig.6) the data is stationary. The plot shows there is more constant level(From Fig.8). We conclude that 80% prediction interval as an dark grey shaded area, and the 95% prediction interval as a light Grey (From Fig.9). From Fig.10 Correlogram it shows that the autocorrelation at lag1, 3 is just touching the significance bounds sowe can carry out a Ljung-Box test. From Fig 12 time series plot there is volatility (original open differencing plot) Histogram for open and closed series are almost same (From Fig.13 and 14) and from Fig 16 and 17 correlation function are in limit. Conclusions of this paper is that time series plot of nestle company is volatile in nature and forecasting values goes on decrease from high price to low price.

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