Quantitative Applications in Finance - Project

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Contents

1 The Company - ACC

Compnay held for analysis is ACC. ACC Limited (Formerly The Associated Cement Companies Limited) one of the largest producers of cement in India. It's registered office is called Cement House. It is located on Maharishi Karve Road, Mumbai. The stock price of company contributes in calculating BSE Sensex.

ACC Ltd is India's foremost manufacturer of cement and concrete. The company is engaged in the manufacture of cement and ready-mixed concrete. They manufacture a range of portland cement for general construction and special applications. In addition, they also offer two products namely, bulk cement and ready mix concrete. The company's operations are spread throughout the country with 16 modern cement factories, more than 40 Ready mix concrete plants, 20 sales offices, and several zonal offices.

Their subsidiaries include ACC Concrete Ltd, Bulk Cement Corporation (India) Ltd, ACC Mineral Resources Ltd, Lucky Minmat Ltd, National Limestone Co Pvt Ltd and Encore Cements & Additives Pvt Ltd. ACC Ltd was incorporated on August 1, 1996 as The Associated Cement Companies Ltd. The company was formed by merger of ten existing cement companies. In the year 1944, they established India's first entirely indigenous cement plant at Chaibasa in Bihar. In the year 1956, they established bulk cement depot at Okhla, Delhi. In the year 1965, the company established Central Research Station at Thane. In the year 1973, they acquired The Cement Marketing Company of India. In the year 1978, they introduced energy efficient precalcinator technology for the first time in India. In the year 1982, the company commissioned their first 1 MTPA plant in the country at Wadi, Karnataka. In the year 1982, the company incorporated Bulk Cement Corporation of India, a joint venture with the Government of India. In the year 1993, they started commercial manufacture of Ready Mixed Concrete at Mumbai. In the year 1999, they commissioned captive power plants at the Jamul and Kymore plants in Madhya Pradesh.

The house of TATA was intimately associated with the company upto 1999. In the year 1999, the Tata group sold their 7.2% stake in the company to Ambuja Cement Holdings Ltd, a subsidiary of Gujarat Ambuja Cements Ltd and in the year 2000, Tata group sold their remaining stake in the company to Gujarat Ambuja Cements Ltd. In the year 2001, the company commissioned a new plant of 2.6 MTPA capacity at Wadi, Karnataka. In the year 2003, IDCOL Cement Ltd becomes a subsidiary of the company, which was renamed as Bargarh Cement Ltd during the year 2004. In the year 2004, the company was named as Consumer Superbrand by the Superbrands Council of India, becoming the only cement company to get this status.

In the year 2005, the company completed the modernization and expansion project at Chaibasa in Jharkhand, replacing old wet process technology with a new 1.2 MTPA clinkering unit, together with a captive power plant of 15 MW. In the year 2006, the subsidiary companies Damodhar Cement & Slag Ltd, Bargarh Cement Ltd and Tarmac (India) Ltd merged with the company. Also, the name of the company was changed from The Associated Cement Companies Ltd to ACC Ltd with effect from September 1, 2006. In the year 2007, the company commissioned wind energy farm in Tamilnadu. In July 2007, the company sold their entire shareholding in their wholly owned subsidiary ACC Nihon Castings Ltd at a consideration of Rs 30 crore to V N Enterprises Ltd of Hindustan Udyog Group. In the year 2008, the ready mixed concrete business was hived off to a new subsidiary called ACC Concrete Ltd. They acquired 40% stake in Alcon Cement Company Pvt Ltd to strengthen their presence in Goa. Also, they acquired 12.41% equity shares of Bulk Cement Corporation (India) Ltd from IDBI Bank Ltd, thereby increasing their shareholding in the said subsidiary company to 94.65%. In March 2008, the company sold their wholly owned subsidiary, ACC Machinery Company Ltd for a consideration of Rs 45 crore. In July 7, 2008, they inaugurated ACC Cement Technology Institute at Jamul. In the year 2009, the company commissioned one 15 MW CPP as a part of Bargarh plant expansion. The additional captive power generating capacity of 50 MW in Wadi, 15 MW in Bargarh and 25 MW in Chanda is scheduled to be commissioned and stabilized in 2010. They inaugurated new Grinding plant of capacity 1.60 million tonnes at Thondebhavi in Karnataka. During the year, the company acquired 100% equity stake in National Limestone Company Pvt Ltd, making it as a wholly owned subsidiary of the company. Also, they acquired 100% equity stake in Encore Cements and Additives Pvt Ltd which has a slag grinding plant in Vishakhapatnam in coastal Andhra Pradesh. Consequently, ECAPL became a wholly owned subsidiary of the company with effect from January 28, 2010.

In September 2009, the company installed and commissioned a coal washery in Jamul. Also, the company is in the process of commissioning a coal washery in the Bargarh plant in 2010. In January 4, 2010, Kudithini Cement Grinding Plant was inaugurated in Karnataka with a capacity of 1.1 MTPA of Portland Slag Cement. In April 2010, the company commissioned a 2.5-MW wind energy farm near Satara, Maharashtra, at a cost of Rs 13 crore. The wind farm has two 1.5-MW turbines. The power from the wind farm will be supplied through a wheeling arrangement to the company's Thane Complex and Bulk Cement Corporation (India) Ltd, a subsidiary company at Kalamboli, near Mumbai. In the year 2010, the company commissioned the the 2.5 MW wind mill project in Maharashtra. Also, they commissioned one CPP of 25 MW at Wadi, two 15 MW CPPs at Bargarh and one 25 MW CPP at Chanda during the year. The company through their wholly owned subsidiary ACC Mineral Resources Ltd entered into joint venture agreements with Madhya Pradesh State Mining Corporation Ltd for development of four coal blocks.

In April 2010, the company completed the acquisition of a 45% equity stake in Asian Concrete and Cements Pvt Ltd. This company commenced production from their new grinding unit during the year. In June 2010, the Financial Express-EVI Green Business Leadership Award 2009-10 was conferred on ACC Ltd for being the 'Best Performer' in the cement category. This award is an acknowledgement of ACC's commitment towards its environmental friendly initiatives in the country. In November 2010, the company commissioned the world's largest kiln with a capacity of 12500 tpd at Wadi in the State of Karnataka. They commenced trial production in the clinkering unit at Chanda in Maharashtra having a kiln capacity of 7000 tpd and commenced commercial production during the first quarter of the financial year 2011. In the year 2011, the company installed the world's largest kiln at Wadi, Karnataka with a capacity of 12,500 tonnes per day. The Operations of the state-of-the-art kiln at Wadi and the cement grinding plants at Kudithini and Thondebhavi stabilized during the year. The new clinkering unit at Chanda in Maharashtra also stabilized its operations during the year. The cement mill at Chanda was successfully commissioned during the year under review and commercial operations have commenced in January 2012 after appropriate ramping up.

In November 2011, the Secretarial and Share Departments of the company received an ISO 9001-2008 certification from Det Norske Veritas (DNV) AS Certification Services. During the year, the company made an application to the Honorable High Court of Judicature at Bombay for approval to a scheme of amalgamation of three of the company's wholly owned subsidiaries viz. Encore Cement and Additives Pvt Ltd, Lucky Minmat Ltd and National Limestone Company Pvt Ltd. The amalgamation process is currently in progress. The company is planning to set up a new clinker production facility of 2.79 MTPA and allied grinding facility at Jamul. The company is also planning decentralized grinding staions which will use clinker produced at Jamul. The project will be implemented in phased manner and scheduled for completion by first quarter of 2015.

Data collected from Bloomberg Terminal consist of the prices and volume of **ACC Stocks**. ACC stocks are traded in the CNX_NIFTY 50.

The head of the data is as follows:

R Terminal

```
        Date   Open   High    Low  Close Volume Adj.Close
1 01-07-2011 952.05 969.90 941.55 955.20 333800    851.99
2 04-07-2011 969.85 969.85 949.05 953.70 278700    850.65
3 05-07-2011 952.05 972.70 952.05 970.70 372100    865.82
4 06-07-2011 970.40 977.90 960.15 963.80 130500    859.66
```

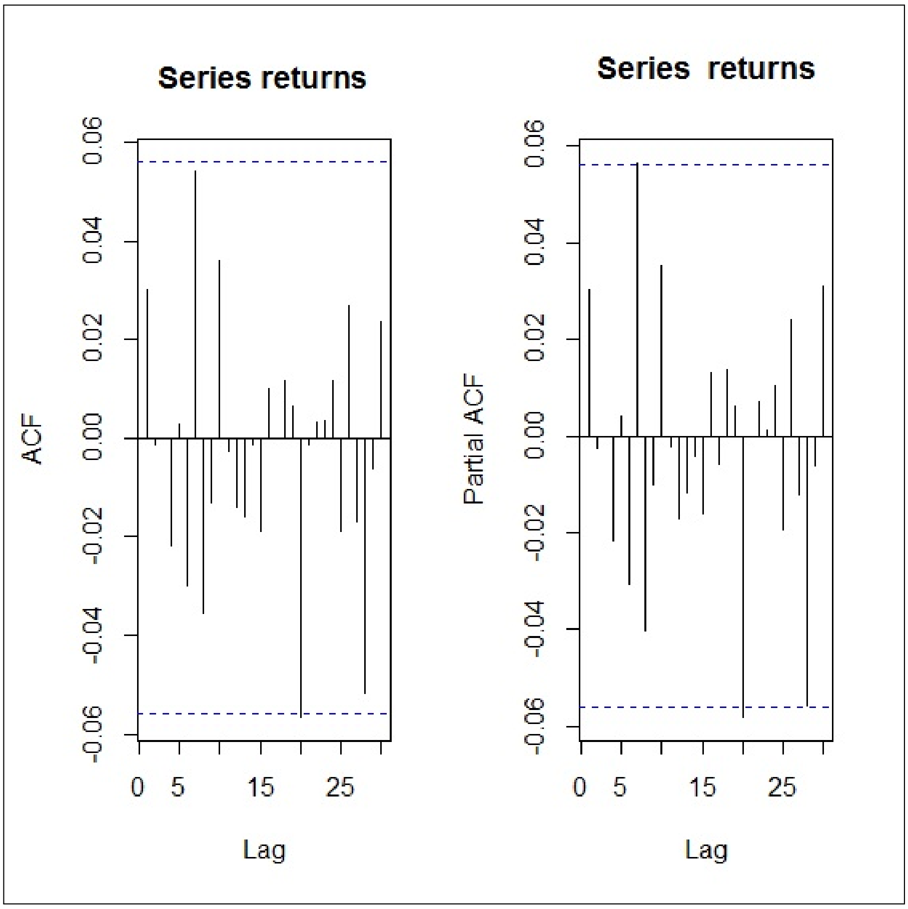
```
5 07-07-2011 964.00 993.70 964.00 991.05 438400    883.97
6 08-07-2011 993.00 998.00 962.60 975.35 315800    869.96
```

---

2 Modelling Returns - Calculation and Stationarity

```
> adf<-adf.test(returns);
Warning message:
In adf.test(returns) : p-value smaller than printed p-value
> adf

        Augmented Dickey-Fuller Test

data:  returns
Dickey-Fuller = -10.365, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

On conducting an ADF test on the logarithimic returns, we find that there is enough evidence to conclude that there is stationarity in the data. The plot of the ACF and PACF is given below.



The plot of ACF & PACF suggest that the probable model will be ARMA(0,0). Next proceeding with the auto.arima function, we see the same.

```
> m1=auto.arima(returns);
> m1
```

```
Series: returns
ARIMA(0,0,0) with non-zero mean

Coefficients:
      intercept
          5e-04
s.e.      5e-04

sigma^2 estimated as 0.0002531:  log likelihood=3337.65
AIC=-6671.3   AICc=-6671.29   BIC=-6661.08
>
```

2.1 Testing of Various Models

We test the following models:

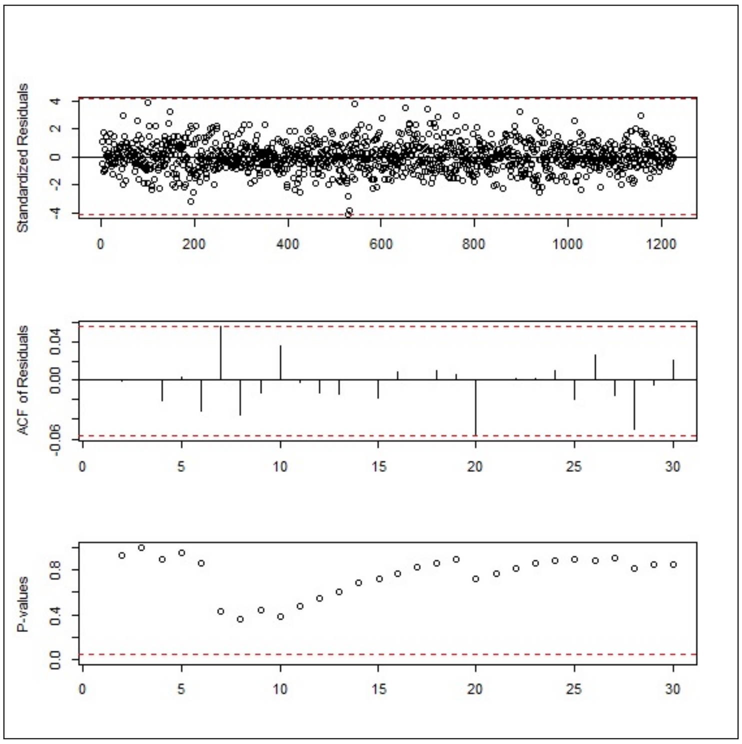
- AR(1)
- MA(1)
- ARMA(1,1)

```
> m2=arima(returns, order=c(1,0,0));
> m3=arima(returns, order=c(0,0,1));
> m4=arima(returns, order=c(1,0,1));
> m2

Call:
arima(x = returns, order = c(1, 0, 0))

Coefficients:
         ar1  intercept
      0.0305      5e-04
s.e.  0.0285      5e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.22,  aic = -6672.45
> m3

Call:
arima(x = returns, order = c(0, 0, 1))

Coefficients:
         ma1  intercept
      0.0306      5e-04
s.e.  0.0286      5e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.23,  aic = -6672.45
> m4

Call:
arima(x = returns, order = c(1, 0, 1))

Coefficients:
```

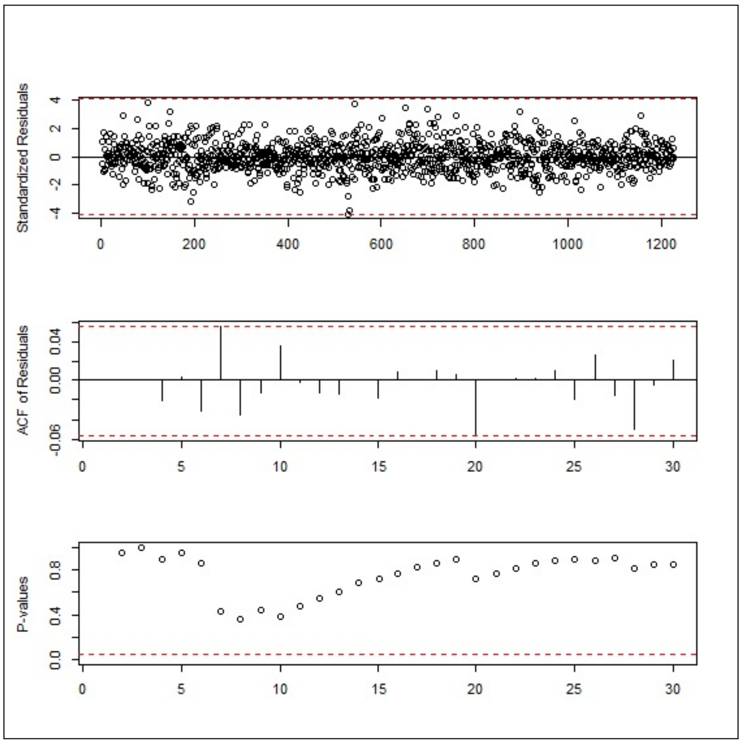
```
         ar1     ma1  intercept
      0.0149  0.0156      5e-04
s.e.  0.9849  0.9869      5e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.22,  aic = -6670.45
>
>
```

From the above four models, MA(1) AR(1) models looks to be the best ones from AIC criteria of comparison. If we observe the LLH, the difference is not very significant between AR(1) and MA(1). Next we observe the results of Ljung-Box Test of residuals.

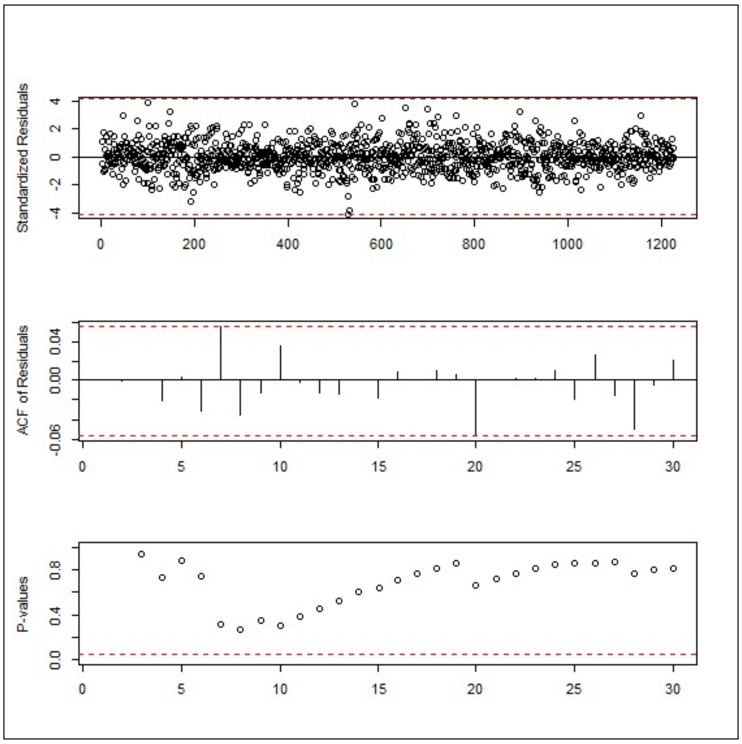
2.2 AR(1) model diagnosis



2.3 MA(1) model diagnosis



2.4 ARMA(1,1) model diagnosis

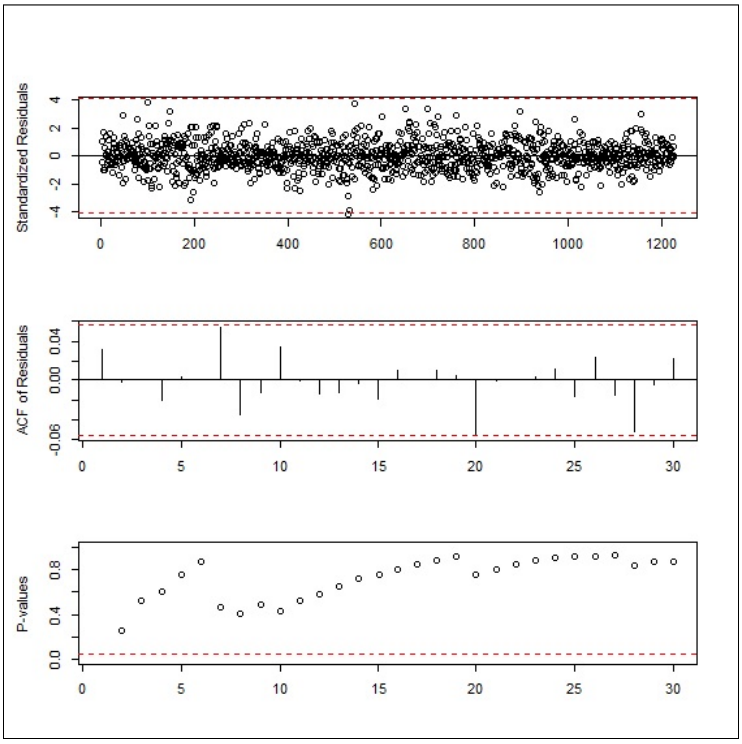


2.5 Analysis

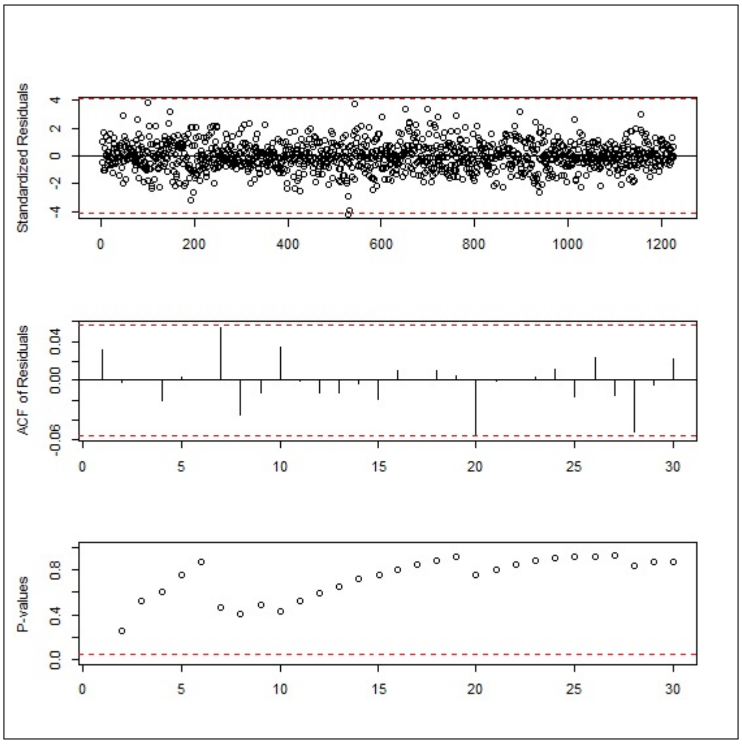
If we look at the p-values of the models, all of them lie above the threshold levels. However, by the ACF we see there is a spike at lag six. This spike was present in the series returns. Thus we need to explore the ARMA models with lag=6.

```
> m8=arima(returns, order=c(6,0,0), fixed=c(0,0,0,0,0,NA,NA))
Warning message:
In arima(returns, order = c(6, 0, 0), fixed = c(0, 0, 0, 0, 0, NA,  :
  some AR parameters were fixed: setting transform.pars = FALSE
> m8

Call:
arima(x = returns, order = c(6, 0, 0), fixed = c(0, 0, 0, 0, 0, NA, NA))

Coefficients:
      ar1  ar2  ar3  ar4  ar5      ar6  intercept
        0    0    0    0    0  -0.0306      5e-04
s.e.    0    0    0    0    0   0.0286      4e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.22,  aic = -6672.45
> m9=arima(returns, order=c(0,0,6), fixed=c(0,0,0,0,0,NA,NA))
> m9

Call:
arima(x = returns, order = c(0, 0, 6), fixed = c(0, 0, 0, 0, 0, NA, NA))

Coefficients:
      ma1  ma2  ma3  ma4  ma5      ma6  intercept
        0    0    0    0    0  -0.0315      5e-04
s.e.    0    0    0    0    0   0.0290      4e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.24,  aic = -6672.48
> m10=arima(returns, order=c(6,0,6), fixed=c(0,0,0,0,0,NA,0,0,0,0,0,NA,NA))
Warning message:
In arima(returns, order = c(6, 0, 6), fixed = c(0, 0, 0, 0, 0, NA,  :
  some AR parameters were fixed: setting transform.pars = FALSE
> m10

Call:
arima(x = returns, order = c(6, 0, 6), fixed = c(0, 0, 0, 0, 0, NA, 0, 0, 0,
    0, 0, NA, NA))

Coefficients:
      ar1  ar2  ar3  ar4  ar5     ar6  ma1  ma2  ma3  ma4  ma5     ma6
        0    0    0    0    0  0.1130    0    0    0    0    0  -0.145
s.e.    0    0    0    0    0  0.5812    0    0    0    0    0   0.582
      intercept
          5e-04
s.e.      4e-04

sigma^2 estimated as 0.0002526:  log likelihood = 3338.29,  aic = -6670.57
>
```

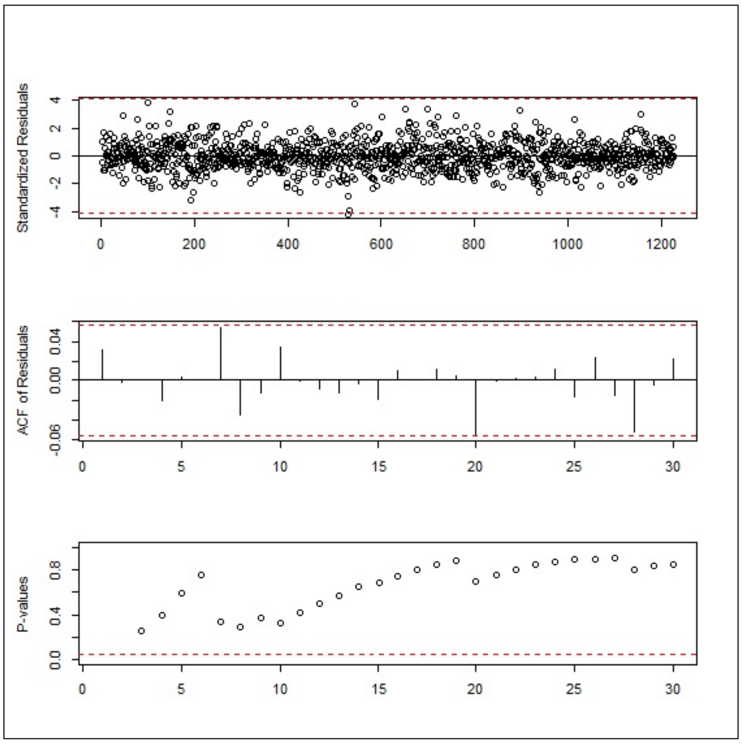
2.6 AR(6) model diagnosis



2.7 MA(6) model diagnosis



2.8 ARMA(6,6) model diagnosis



2.9 Model Summary

Model	ARMA(0,0)	AR(1)	MA(1)	ARMA(1,1)	AR(6)	MA(6)	ARMA(6,6)
AIC	-6671.3	-6672.45	-6672.45	-6670.45	-6672.45	**-6672.48**	-6670.57
LLH	3337.65	3338.22	3338.23	3338.22	3338.22	3338.24	3338.29

Thus we can see that the ARMA(6,6) is best in terms of AIC. Also, its diagonosis of residuals show that the residuals are a white noise. (p-values lie above threshold.) Next we proceed for returns forecasting with ARMA(0,0), ARMA(6,6), AR(6), MA(6) models.

3 Returns Forecasting

One day ahead returns are forecasted and written to a separate file. The summary of the results is as follows:

Models	ARMA(0,0)	AR(6)	MA(6)	ARMA(6,6)
AIC	-6671.3	-6672.45	**-6672.48**	-6670.57
RMSE	**0.012876721**	0.01291133	0.012905592	**0.013139689**
Sign Prediction	48%	52%	52%	**57%**
Direction Prediction	76%	76%	76%	**81%**

```
for(i in 1:22){m=arima(returns[(i+1):(1216+i)], c(0,0,0)); results[i
    ]=predict(m)$pred[1]};
```

The forecasts are tested for two things:

- Direction
- Sign

The calculation is done in a separate spreadsheet attached.

4 Volatility Modelling

4.1 The ARCH Effect

Before moving on to the GARCH models, we test the retunrns for ARCH effects using the arch test. Following is result:

```
> arch<-ArchTest(returns);
> arch

        ARCH LM-test; Null hypothesis: no ARCH effects

data:  returns
Chi-squared = 37.613, df = 12, p-value = 0.0001776

>
```

The associated p-value happens to be small enough for us to reject the Null hypothesis: no ARCH effects. Thus we can **conclude that there is ARCH effect in the returns**. Next we continue with volatlity models, exploiting this ARCH effect.

4.2 GARCH(1,1) with Normal Distribution

```
s1<- ugarchspec(variance.model=list(model="sGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="norm");
mv1<-ugarchfit(s1,returns);
```

```
> mv1

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000686    0.000450   1.5248  0.12730
ar1     0.038656    0.029857   1.2947  0.19542
omega   0.000014    0.000001  27.5468  0.00000
alpha1  0.056257    0.005201  10.8157  0.00000
beta1   0.886970    0.010385  85.4062  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000686    0.000419   1.6387  0.10128
ar1     0.038656    0.030185   1.2807  0.20031
```

```
omega   0.000014    0.000001  24.5132  0.00000
alpha1  0.056257    0.004924  11.4249  0.00000
beta1   0.886970    0.009616  92.2402  0.00000

LogLikelihood : 3357.247

Information Criteria
------------------------------------

Akaike       -5.4686
Bayes        -5.4477
Shibata      -5.4686
Hannan-Quinn -5.4607

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.03058  0.8612
Lag[2*(p+q)+(p+q)-1][2]   0.05388  1.0000
Lag[4*(p+q)+(p+q)-1][5]   0.51334  0.9931
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.4346  0.5097
Lag[2*(p+q)+(p+q)-1][5]    1.4696  0.7474
Lag[4*(p+q)+(p+q)-1][9]    2.3196  0.8636
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.455 0.500 2.000  0.2278
ARCH Lag[5]     1.746 1.440 1.667  0.5301
ARCH Lag[7]     1.820 2.315 1.543  0.7554

Nyblom stability test
------------------------------------
Joint Statistic:  76.2098
Individual Statistics:
mu     0.10111
ar1    0.08593
omega  5.75349
alpha1 0.16093
beta1  0.21953

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.28 1.47 1.88
Individual Statistic:    0.35 0.47 0.75
```

```
Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias          1.22149 0.2221
Negative Sign Bias 1.39168 0.1643
Positive Sign Bias 0.09768 0.9222
Joint Effect       2.38069 0.4972


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     32.04      0.03091
2    30     42.12      0.05473
3    40     51.65      0.08452
4    50     66.50      0.04867


Elapsed time : 0.3643231
```

Analysis: The model estimated is:

Mean Equation:

$$r_t = e_t \tag{1}$$

The distrubution assumption is normal. The volatlity eqaution is:

$$\sigma_t^2 = 0.000014 + 0.056257\epsilon_{t-1}^2 + 0.886970\sigma_{t-1}^2 \tag{2}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability Failed; Omega not stable over time
Pearson Goodness-of-Fit	p-values significant upto 97% CI, i.e. distribution is normal

4.3 GARCH(1,1) with GED

```
s2<- ugarchspec(variance.model=list(model="sGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="sged");
mv2<-ugarchfit(s2,returns);
```

```
> mv2

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*
```

```
Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : sged

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000669    0.000444  1.50605  0.13206
ar1     0.024834    0.028487  0.87176  0.38334
omega   0.000015    0.000001 16.01003  0.00000
alpha1  0.063131    0.007444  8.48047  0.00000
beta1   0.878560    0.013863 63.37273  0.00000
skew    1.099208    0.036843 29.83531  0.00000
shape   1.503145    0.087970 17.08708  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000669    0.000418  1.59864  0.10990
ar1     0.024834    0.028498  0.87142  0.38353
omega   0.000015    0.000001 15.58382  0.00000
alpha1  0.063131    0.006006 10.51102  0.00000
beta1   0.878560    0.010515 83.55010  0.00000
skew    1.099208    0.037257 29.50349  0.00000
shape   1.503145    0.089322 16.82829  0.00000

LogLikelihood : 3372.551

Information Criteria
------------------------------------

Akaike       -5.4903
Bayes        -5.4611
Shibata      -5.4904
Hannan-Quinn -5.4793

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.06750  0.7950
Lag[2*(p+q)+(p+q)-1][2]   0.09014  1.0000
Lag[4*(p+q)+(p+q)-1][5]   0.55951  0.9909
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2264  0.6342
Lag[2*(p+q)+(p+q)-1][5]    1.5339  0.7316
```

```
Lag[4*(p+q)+(p+q)-1][9]    2.4430  0.8461
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.767 0.500 2.000  0.1837
ARCH Lag[5]     2.279 1.440 1.667  0.4128
ARCH Lag[7]     2.348 2.315 1.543  0.6439

Nyblom stability test
------------------------------------
Joint Statistic:  62.2484
Individual Statistics:
mu     0.07506
ar1    0.08993
omega  4.35013
alpha1 0.14353
beta1  0.18260
skew   0.06365
shape  0.06936

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.69 1.9 2.35
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.9492 0.3427
Negative Sign Bias  1.1273 0.2598
Positive Sign Bias  0.1116 0.9112
Joint Effect        1.4774 0.6875


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20      9.40       0.9662
2    30     31.21       0.3556
3    40     35.08       0.6495
4    50     50.10       0.4295


Elapsed time : 0.913667

>
```

Analysis: The model estimated is:

Mean Equation:

$$r_t = e_t \tag{3}$$

The distrubution assumption is GED(1.099, 1.503). The volatlity eqaution is:

$$\sigma_t^2 = 0.000015 + 0.063131\epsilon_{t-1}^2 + 0.878560\sigma_{t-1}^2 \tag{4}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability Failed; Omega not stable over time
Pearson Goodness-of-Fit	p-values insignificant, i.e. distribution is not GED

4.4 eGARCH(1,1) with Normal Distribution

```
#eGARCH MODEL FITTING+norm distribution
s3<- ugarchspec(variance.model=list(model="eGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="norm");
mv3<-ugarchfit(s3,returns);
```

```
 > mv3

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : eGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000479    0.000453   1.0583 0.289927
ar1     0.035008    0.029356   1.1925 0.233049
omega  -0.421553    0.055236  -7.6319 0.000000
alpha1 -0.031458    0.016426  -1.9151 0.055482
beta1   0.948921    0.006642 142.8762 0.000000
gamma1  0.120366    0.026494   4.5432 0.000006

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000479    0.000438   1.0940 0.273949
ar1     0.035008    0.029710   1.1783 0.238668
omega  -0.421553    0.021549 -19.5622 0.000000
alpha1 -0.031458    0.019910  -1.5800 0.114114
beta1   0.948921    0.002558 370.9843 0.000000
```

```
gamma1  0.120366    0.027978   4.3022 0.000017

LogLikelihood : 3359.447

Information Criteria
------------------------------------

Akaike       -5.4706
Bayes        -5.4455
Shibata      -5.4706
Hannan-Quinn -5.4611

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.009487  0.9224
Lag[2*(p+q)+(p+q)-1][2]  0.021519  1.0000
Lag[4*(p+q)+(p+q)-1][5]  0.411840  0.9967
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.6861  0.4075
Lag[2*(p+q)+(p+q)-1][5]    1.8822  0.6465
Lag[4*(p+q)+(p+q)-1][9]    2.9561  0.7662
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.340 0.500 2.000  0.2470
ARCH Lag[5]     1.749 1.440 1.667  0.5295
ARCH Lag[7]     1.928 2.315 1.543  0.7326

Nyblom stability test
------------------------------------
Joint Statistic:  0.907
Individual Statistics:
mu     0.12302
ar1    0.07111
omega  0.27317
alpha1 0.07445
beta1  0.28177
gamma1 0.07318

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
Individual Statistic:    0.35 0.47 0.75
```

```
Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.9266 0.3543
Negative Sign Bias  0.8513 0.3948
Positive Sign Bias  0.4593 0.6461
Joint Effect        2.1684 0.5382


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     28.81      0.06899
2    30     42.71      0.04840
3    40     52.17      0.07720
4    50     61.36      0.11074


Elapsed time : 0.3402381
```

Analysis: The model estimated is:

Mean Equation:

$$r_t = e_t \tag{5}$$

The distrubution assumption is normal. The volatlity eqaution is:

$$\log \sigma_t^2 = -0.421553 + 0.948921 \log \sigma_{t-1}^2 + .0120366 \frac{\epsilon_{t-1}}{\sigma_{t-1}} \tag{6}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability fails; Individual coeffecients are stable.
Pearson Goodness-of-Fit	p-values insignificant, i.e. distribution is not normal, p-value are quite low though.

4.5 eGARCH(1,1) with sGED

```
#eGARCH MODEL FITTING+sGED distribution
s4<- ugarchspec(variance.model=list(model="eGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="sged");
mv4<-ugarchfit(s4,returns);
```

```
> mv4

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*
```

```
Conditional Variance Dynamics
-----------------------------------
GARCH Model     : eGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : sged

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000535    0.000417  1.28429 0.199042
ar1     0.020988    0.027493  0.76340 0.445225
omega  -0.441037    1.018291 -0.43312 0.664931
alpha1 -0.029756    0.019467 -1.52853 0.126380
beta1   0.947005    0.122081  7.75716 0.000000
gamma1  0.132130    0.205873  0.64180 0.521000
skew    1.098145    0.098339 11.16689 0.000000
shape   1.520196    0.520665  2.91972 0.003503

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.000535    0.001826  0.293049  0.76948
ar1     0.020988    0.075472  0.278092  0.78094
omega  -0.441037   11.413435 -0.038642  0.96918
alpha1 -0.029756    0.072070 -0.412875  0.67970
beta1   0.947005    1.368322  0.692092  0.48888
gamma1  0.132130    2.310871  0.057178  0.95440
skew    1.098145    1.166720  0.941224  0.34659
shape   1.520196    5.887629  0.258202  0.79625

LogLikelihood : 3373.902

Information Criteria
------------------------------------

Akaike       -5.4909
Bayes        -5.4575
Shibata      -5.4910
Hannan-Quinn -5.4783

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2834  0.5945
Lag[2*(p+q)+(p+q)-1][2]    0.2946  0.9946
Lag[4*(p+q)+(p+q)-1][5]    0.6865  0.9826
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
```

```
                        statistic p-value
Lag[1]                     0.4771  0.4897
Lag[2*(p+q)+(p+q)-1][5]    1.8546  0.6532
Lag[4*(p+q)+(p+q)-1][9]    2.9332  0.7699
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.627 0.500 2.000  0.2022
ARCH Lag[5]     2.234 1.440 1.667  0.4218
ARCH Lag[7]     2.373 2.315 1.543  0.6386

Nyblom stability test
------------------------------------
Joint Statistic:  1.0081
Individual Statistics:
mu     0.08409
ar1    0.08500
omega  0.22468
alpha1 0.09138
beta1  0.23106
gamma1 0.08625
skew   0.06220
shape  0.06769

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.89 2.11 2.59
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.8982 0.3692
Negative Sign Bias  0.7511 0.4527
Positive Sign Bias  0.3062 0.7595
Joint Effect        1.7236 0.6317


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     12.11       0.8810
2    30     20.15       0.8882
3    40     47.02       0.1771
4    50     56.63       0.2118


Elapsed time : 1.14781

>
```

Analysis: The model estimated is:
Mean Equation:

$$r_t = -0.000615 + e_t \tag{7}$$

The distrubution assumption is GED(1.098145,1.520196) . The volatlity eqaution is:

$$\log \sigma_t^2 = 0.947005 \log \sigma_{t-1}^2 \tag{8}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability hold at 10%; Individual coeffecients stable at 10%
Pearson Goodness-of-Fit	p-values significant, i.e. distribution is GED

4.6 gjrGARCH(1,1) with Normal Distribution

```
s5<- ugarchspec(variance.model=list(model="gjrGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="norm");
mv5<-ugarchfit(s5,returns);
```

```
> mv5

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : gjrGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000552    0.000452   1.2213 0.221966
ar1     0.037527    0.029484   1.2728 0.203101
omega   0.000014    0.000000  34.0415 0.000000
alpha1  0.036173    0.009979   3.6250 0.000289
beta1   0.889257    0.009832  90.4470 0.000000
gamma1  0.042611    0.021789   1.9556 0.050512

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000552    0.000436   1.2678 0.204869
ar1     0.037527    0.029685   1.2642 0.206173
omega   0.000014    0.000000  33.5763 0.000000
```

```
alpha1  0.036173    0.010354   3.4937 0.000476
beta1   0.889257    0.009167  97.0098 0.000000
gamma1  0.042611    0.023861   1.7858 0.074127

LogLikelihood : 3359.194

Information Criteria
------------------------------------

Akaike       -5.4701
Bayes        -5.4451
Shibata      -5.4702
Hannan-Quinn -5.4607

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.004359  0.9474
Lag[2*(p+q)+(p+q)-1][2]  0.026704  1.0000
Lag[4*(p+q)+(p+q)-1][5]  0.503445  0.9935
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.3596  0.5487
Lag[2*(p+q)+(p+q)-1][5]    1.5441  0.7290
Lag[4*(p+q)+(p+q)-1][9]    2.7081  0.8060
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.245 0.500 2.000  0.2645
ARCH Lag[5]     1.830 1.440 1.667  0.5101
ARCH Lag[7]     1.990 2.315 1.543  0.7194

Nyblom stability test
------------------------------------
Joint Statistic:  78.8543
Individual Statistics:
mu     0.11681
ar1    0.07166
omega  7.00901
alpha1 0.17349
beta1  0.22470
gamma1 0.18108

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.49 1.68 2.12
```

```
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.8313 0.4060
Negative Sign Bias  0.8280 0.4078
Positive Sign Bias  0.3822 0.7024
Joint Effect        1.6681 0.6440


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     34.82      0.01470
2    30     44.03      0.03644
3    40     50.02      0.11116
4    50     65.19      0.06064


Elapsed time : 0.5383792
```

Analysis: The model estimated is:

Mean Equation:

$$r_t = e_t \tag{9}$$

The distrubution assumption is normal. The volatlity eqaution is:

$$\sigma_t^2 = 0.000014 + 0.036173\epsilon_{t-1}^2 + 0.889257\sigma_{t-1}^2 \tag{10}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability Failed; Omega not stable over time
Pearson Goodness-of-Fit	p-values insignificant (with a low confidence intreval), i.e. distribution is not normal

4.7 gjrGARCH(1,1) with GED

```
#gjrGARCH MODEL FITTING+sGED distribution
s6<- ugarchspec(variance.model=list(model="gjrGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="sged");
mv6<-ugarchfit(s6,returns);
```

```
> mv6
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : gjrGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : sged

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000573    0.000446   1.2857 0.198556
ar1     0.022371    0.028084   0.7966 0.425683
omega   0.000015    0.000001  17.6360 0.000000
alpha1  0.044600    0.012762   3.4949 0.000474
beta1   0.878511    0.013675  64.2405 0.000000
gamma1  0.041098    0.027068   1.5183 0.128931
skew    1.100155    0.037998  28.9529 0.000000
shape   1.522247    0.090428  16.8339 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000573    0.000435  1.31748 0.187679
ar1     0.022371    0.027879  0.80244 0.422299
omega   0.000015    0.000001 18.97761 0.000000
alpha1  0.044600    0.011700  3.81180 0.000138
beta1   0.878511    0.010499 83.67320 0.000000
gamma1  0.041098    0.027602  1.48897 0.136496
skew    1.100155    0.038905 28.27813 0.000000
shape   1.522247    0.093800 16.22859 0.000000

LogLikelihood : 3373.708

Information Criteria
------------------------------------

Akaike       -5.4906
Bayes        -5.4572
Shibata      -5.4906
Hannan-Quinn -5.4780

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1589  0.6902
Lag[2*(p+q)+(p+q)-1][2]    0.1791  0.9992
Lag[4*(p+q)+(p+q)-1][5]    0.6608  0.9845
d.o.f=1
H0 : No serial correlation
```

```
Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1587  0.6903
Lag[2*(p+q)+(p+q)-1][5]    1.6035  0.7144
Lag[4*(p+q)+(p+q)-1][9]    2.8002  0.7915
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.618 0.500 2.000  0.2034
ARCH Lag[5]     2.487 1.440 1.667  0.3732
ARCH Lag[7]     2.620 2.315 1.543  0.5879

Nyblom stability test
------------------------------------
Joint Statistic:  63.6768
Individual Statistics:
mu     0.08014
ar1    0.08101
omega  4.82596
alpha1 0.15252
beta1  0.18143
gamma1 0.15038
skew   0.06013
shape  0.06833

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         1.89 2.11 2.59
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias           0.8105 0.4178
Negative Sign Bias  0.6989 0.4848
Positive Sign Bias  0.1865 0.8521
Joint Effect        1.2215 0.7478


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     9.824       0.9572
2    30    22.206       0.8116
3    40    39.579       0.4440
4    50    58.910       0.1570
```

```
Elapsed time : 2.279616
```

Analysis: The model estimated is:
Mean Equation:

$$r_t = e_t \tag{11}$$

The distrubution assumption is GED(1.100155, 1.522247). The volatlity eqaution is:

$$\sigma_t^2 = 0.000015 + 0.044600\epsilon_{t-1}^2 + 0.878511\sigma_{t-1}^2 \tag{12}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability Failed; Omega not stable over time
Pearson Goodness-of-Fit	p-values significant, i.e. distribution is GED

4.8 GARCH(1,1) with $\alpha_1 + \beta_1 = 1$

```
#EWMA estimation
s7<-ugarchspec(mean.model=list(armaOrder=c(1,0), include.mean=TRUE),
    variance.model=list(model="iGARCH",garchOrder=c(1,1),submodel="
  GARCH"), fixed.pars=list(alpha1=1-0.94, omega=0));
mv7<-ugarchfit(s7,returns);
```

```
> mv7

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : iGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000797    0.000456   1.7455 0.080893
ar1     0.045277    0.029479   1.5359 0.124561
omega   0.000000          NA       NA       NA
alpha1  0.060000          NA       NA       NA
beta1   0.940000          NA       NA       NA

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000797    0.000523   1.5229  0.12778
```

```
ar1     0.045277    0.033983   1.3323  0.18275
omega   0.000000          NA       NA       NA
alpha1  0.060000          NA       NA       NA
beta1   0.940000          NA       NA       NA

LogLikelihood : 3344.437

Information Criteria
------------------------------------

Akaike       -5.4526
Bayes        -5.4442
Shibata      -5.4526
Hannan-Quinn -5.4495

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.01759  0.8945
Lag[2*(p+q)+(p+q)-1][2]   0.10711  0.9999
Lag[4*(p+q)+(p+q)-1][5]   0.59279  0.9890
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.5184  0.4715
Lag[2*(p+q)+(p+q)-1][5]    1.4047  0.7633
Lag[4*(p+q)+(p+q)-1][9]    2.0286  0.9016
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.7977 0.500 2.000  0.3718
ARCH Lag[5]    1.6399 1.440 1.667  0.5563
ARCH Lag[7]    1.8061 2.315 1.543  0.7583

Nyblom stability test
------------------------------------
Joint Statistic:  0.1468
Individual Statistics:
mu  0.09132
ar1 0.05872

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         0.61 0.749 1.07
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
```

```
------------------------------------
                   t-value   prob sig
Sign Bias           1.1309 0.2583
Negative Sign Bias  0.8562 0.3920
Positive Sign Bias  0.5581 0.5769
Joint Effect        1.3713 0.7123


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     33.18      0.02289
2    30     37.96      0.12314
3    40     44.28      0.25872
4    50     54.51      0.27312


Elapsed time : 0.04303002
```

Analysis: The model estimated is:
Mean Equation:

$$r_t = e_t \tag{13}$$

The distrubution assumption is normal. The volatlity eqaution is:

$$\sigma_t^2 = 0.06\epsilon_{t-1}^2 + 0.94\sigma_{t-1}^2 \tag{14}$$

Test	**Results**
LB Test Standardized Residuals	Insignificant p-values present, i.e Mean Model is good.
LB Test Standardized Squared Residuals	Insignificant p-values present, i.e. Variance Model is good, all ARCH effect captured.
Nyblom Stability Test	Joint Stability achieved; Individual coeffecients stable over time
Pearson Goodness-of-Fit	p-values significant, i.e. distribution is normal

5 SSRV Volatlity Benchmarking

SSRV volatlity was achieved with the help of the following R code.

```
#SSRV Volatility Benchmark
rv=matrix("na", 21, 1);
for(i in 0:21){rv[i+1]=sum((returns_hf[((75*i)+1):((i*75)+75)])^2)};
#developing scalining factor.#
realised_variance=sum(as.numeric(rv[1:21]));
close_returns_variation=sum((returns_hf[1:21]-mean(returns_hf[1:21])
    )^2);
scale=close_returns_variation/realised_variance;
ssrv=as.numeric(rv)*scale;
ssrv=sqrt(ssrv*1);
```

The following 21 day SSRV was obtained.

```
sl. SSRV
1 0.000888619
2 0.000654024
3 0.000657209
4 0.000431798
5 0.000727497
6 0.000580572
7 0.000634128
8 0.000968227
9 0.000619285
10 0.000489875
11 0.000668381
12 0.001206758
13 0.000768732
14 0.000648425
15 0.000546097
16 0.000774491
17 0.001274189
18 0.001263921
19 0.001311695
20 0.00073394
21 0.000785342
```

6 Volatility Forecasting

One period ahead Volatlity Forecasting for 21 days (1 month) is done using the seven models stated before.

```
for(i in 1:22 ){mvol=ugarchfit(s1, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv1.csv');
```

The following table summarises the forecasting results:

Model	BIC	RMSE	Direction
sGARCH(1,1)	-5.4477	0.012726833	50%
sGARCH(1,1)_GED	**-5.4611**	0.012632365	50%
eGARCH(1,1)	-5.4455	0.012606287	50%
eGARCH(1,1)_GED	-5.4575	0.012566524	50%
gjrGARCH(1,1)	-5.4451	0.01238545	50%
gjrGARCH(1,1)_GED	-5.4572	0.012316509	50%
EWMA(1,1)	-5.4442	0.010315653	50%

Based on BIC sGARCH with GED distribution seems to be the best model here. All the garch models have a 50% directional accuracy.The calculations have been provided in the attached spreadsheet.

7 Final Summary

The best volatility model happens to be sGARCH(1,1)_GED based on BIC. The best return equation is ARMA(6,6) based on sign and direction prediction. By AIC, we have MA(6).

Consolidated R-Script

```
#=====================ADD LIBRARIES=====================================
library('TSA');
library('forecast');
library('tseries');
library('moments');
library('lmtest');
library('sandwich');
library('qcc');
library('rugarch');
library('FinTS');
library('xts');
#========================Data File & ADF test ==========================
x=read.csv(file.choose(), sep=",", h=T)#read _ohlc files
y=read.csv(file.choose(), sep=",", h=T)# read the file containing 5
    minute price data from 920 t0 1530 Hrs. for the month of June,
    2014#
#z=read.csv(file.choose(), sep=",", h=T)# read the file containing
    close-to-close returns data for the month of June, 2014#
#calculate the returns
returns<-diff(log(x$Adj.Close), lag=1);#price log returns
returns_hf<-diff(log(y$Close),lag=1);#high frequency price log
    returns
adf<-adf.test(returns);
par(mfrow=c(1,2));
acf(returns);
pacf(returns);
#==================Determine the mean equation==========================
m1=auto.arima(returns);
m2=arima(returns, order=c(1,0,0));
m3=arima(returns, order=c(0,0,1));
m4=arima(returns, order=c(1,0,1));
tsdiag(m1);
tsdiag(m2);
tsdiag(m3);
tsdiag(m4);
#futher analysis of means
m8=arima(returns, order=c(6,0,0), fixed=c(0,0,0,0,0,NA,NA));
m9=arima(returns, order=c(0,0,6), fixed=c(0,0,0,0,0,NA,NA));
m10=arima(returns, order=c(6,0,6), fixed=c(0,0,0,0,0,NA,0,0,0,0,0,NA
    ,NA));
tsdiag(m8);
tsdiag(m9);
tsdiag(m10);
#============Returns Forecast
    ==================================================

results=matrix("na",nrow = 22, ncol = 1);
#forecasting ARMA(0,0)
for(i in 1:22){m=arima(returns[(i+1):(1216+i)], c(0,0,0)); results[i
    ]=predict(m)$pred[1]};
```

```r
write.csv(results, "m1.csv");
#forecasting ARMA(6,0)
for(i in 1:22){m=arima(returns[(i+1):(1216+i)], c(6,0,0)); results[i
   ]=predict(m)$pred[1]};
write.csv(results, "m2.csv");
#forecasting ARMA(0,6)
for(i in 1:22){m=arima(returns[(i+1):(1216+i)], c(0,0,6)); results[i
   ]=predict(m)$pred[1]};
write.csv(results, "m3.csv");
#forecasting ARMA(6,6)
for(i in 1:22){m=arima(returns[(i+1):(1216+i)], c(6,0,6)); results[i
   ]=predict(m)$pred[1]};
write.csv(results, "m4.csv");

#===============Volatility Modelling
   =========================================
#condunt the ARCH test
arch<-ArchTest(returns);
#
   ===================================================================================

  #sGARCH MODEL FITTING+normal distribution
s1<- ugarchspec(variance.model=list(model="sGARCH", garchOrder=c
   (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
   include.mean=T), distribution="norm");
mv1<-ugarchfit(s1,returns);
#sGARCH MODEL FITTING+sGED distribution
s2<- ugarchspec(variance.model=list(model="sGARCH", garchOrder=c
   (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
   include.mean=T), distribution="sged");
mv2<-ugarchfit(s2,returns);
#
   ===================================================================================

#eGARCH MODEL FITTING+norm distribution
s3<- ugarchspec(variance.model=list(model="eGARCH", garchOrder=c
   (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
   include.mean=T), distribution="norm");
mv3<-ugarchfit(s3,returns);
#eGARCH MODEL FITTING+sGED distribution
s4<- ugarchspec(variance.model=list(model="eGARCH", garchOrder=c
   (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
   include.mean=T), distribution="sged");
mv4<-ugarchfit(s4,returns);
#
   ===================================================================================

#gjrGARCH MODEL FITTING+norm distribution
s5<- ugarchspec(variance.model=list(model="gjrGARCH", garchOrder=c
   (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
   include.mean=T), distribution="norm");
```

```
mv5<-ugarchfit(s5,returns);
#gjrGARCH MODEL FITTING+sGED distribution
s6<- ugarchspec(variance.model=list(model="gjrGARCH", garchOrder=c
    (1,1),submodel="GARCH"), mean.model=list(armaOrder=c(1,0),
    include.mean=T), distribution="sged");
mv6<-ugarchfit(s6,returns);
#
    ==========================================================================

#EWMA estimation
s7<-ugarchspec(mean.model=list(armaOrder=c(1,0), include.mean=TRUE),
     variance.model=list(model="iGARCH",garchOrder=c(1,1),submodel="
    GARCH"), fixed.pars=list(alpha1=1-0.94, omega=0));
mv7<-ugarchfit(s7,returns);
#
    ==========================================================================

#SSRV Volatility Benchmark
rv=matrix("na", 21, 1);
for(i in 0:21){rv[i+1]=sum((returns_hf[((75*i)+1):((i*75)+75)])^2)};
#developing scalining factor.#
realised_variance=sum(as.numeric(rv[1:21]));
close_returns_variation=sum((returns_hf[1:22]-mean(returns_hf[1:22])
    )^2);
scale=close_returns_variation/realised_variance;
ssrv=as.numeric(rv)*scale;
annualised_ssrv=sqrt(ssrv*1);
write.csv(annualised_ssrv, "annualised_ssrv.csv");
#
    ==========================================================================

#Forcasting volatility using models
for(i in 1:22 ){mvol=ugarchfit(s1, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv1.csv');

for(i in 1:22 ){mvol=ugarchfit(s2, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv2.csv');

for(i in 1:22 ){mvol=ugarchfit(s3, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv3.csv');

for(i in 1:22 ){mvol=ugarchfit(s4, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv4.csv');

for(i in 1:22 ){mvol=ugarchfit(s5, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv5.csv');
```

```
for(i in 1:22 ){mvol=ugarchfit(s6, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv6.csv');

for(i in 1:22 ){mvol=ugarchfit(s7, data=returns[(1+i):(1204+i)]);
    results[i]=sigma(ugarchforecast(mvol, n.ahead=1))[1]};
write.csv(results, 'mv7.csv');
```