REPORT

Time Series Forecasting of Ultratech Cement

By

Serial Number 20

Under The Supervision Of

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(DEC 2022)

FIN F414
FINANCIAL RISK ANALYTICS & MANAGEMENT

ACKNOWLEDGEMENT

We would like to express my sincerest gratitude to Dr. Nagaraju Thota, sir, for giving us an opportunity for this project and his valuable time to provide us the required guidance whenever required. His input through classes, notes, and slides proved to be very vital for the project. We would like to thank him for providing us with such an excellent opportunity to apply our course knowledge to real-life instances and get hands-on experience. We are indebted for all his help and guidance throughout the course and this assignment.

ABOUT THE COMPANY

Nature of business

UltraTech Cement Limited is an India-based company engaged in the business of cement and cement related products. The Company manufactures a range of products that cater to construction needs from foundation to finish, including Ordinary Portland Cement (OPC), Portland Blast Furnace Slag Cement (PSC), Portland Pozzolana Cement (PPC), white cement and white cement-based products, ready mix concrete, including specialty concrete, building products, such as aerated autoclaved concrete (AAC) blocks and joining mortars and a host of others in retail formats. The Company's products include UltraTech Cement, UltraTech Concrete, UltraTech Building Products, Birla White Cement and White Topping Concrete. Its UltraTech Building products range includes tiles adhesives, repair products (MICROKRETE and BASEKRETE), waterproofing products, industrial and precision grout, plasters (READIPLAST, SUPER STUCCO), masonry products (FIXOBLOCK), lightweight autoclaved aerated concrete block.

Ownership Pattern

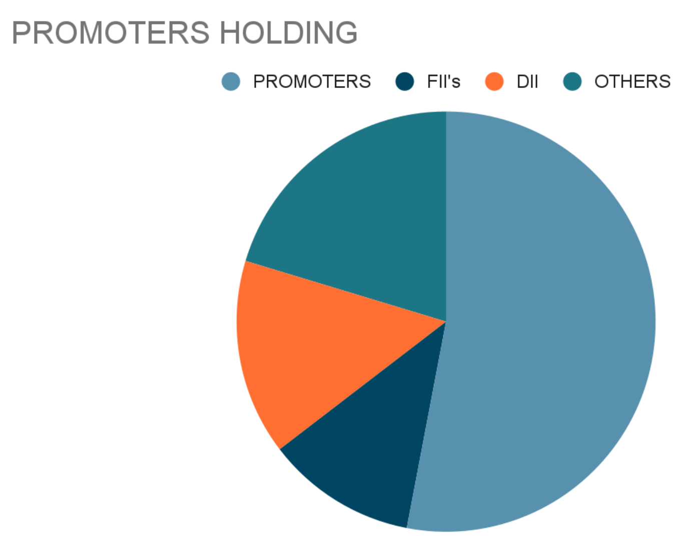
Ultratech cement is a public limited company.Aditya birla group holds the majority of the shares.

Promoters - 59.6% - Aditya Birla group

FII - 13.12%

DII- 17.04%

OTHERS - 23%



Importance in Industry

India is the second largest producer of cement in the world. No wonder, India's cement industry is a vital part of its economy, providing employment to more than a million people, directly or indirectly. Ever since it was deregulated in 1982, the Indian cement industry has attracted huge investments, both from Indian as well as foreign investors. India has a lot of potential for development in the infrastructure and construction sector and the cement sector is expected to largely benefit from it. Some of the recent major initiatives such as development of 98 smart cities are expected to provide a major boost to the sector. Expecting such developments in the country and aided by suitable government foreign policies, several foreign players such as Lafarge-Holcim, Heidelberg Cement, and Vicat have invested in the country in the recent past. A significant factor which aids the growth of this sector is the ready availability of the raw materials for making cement, such as limestone and coal..

1.6 Board of directors:

Mr.Kumar Mangalam Birla	**Chairman**
Mr.Ashish Dwivedi	**Chief Executive Officer**
Mr.Ramesh Mitragotri	**Chief Human Resource Officer**
Mr.Sujeet Jai	**Chief Legal Officer**
Mr.E R Raj Narayanan	**Chief Manufacturing Officer**
Mr.Vivek Agrawal	**Chief Marketing Officer**
Mr.Sanjeeb Kumar Chatterjee	**Co. Secretary & Compl. Officer**
Mr.Pramod Rajgaria	**President**
Mr.Sunil Duggal	**Independent Director**

Mr.K C Jhanwar	Managing Director

DAILY RETURNS ANALYSIS

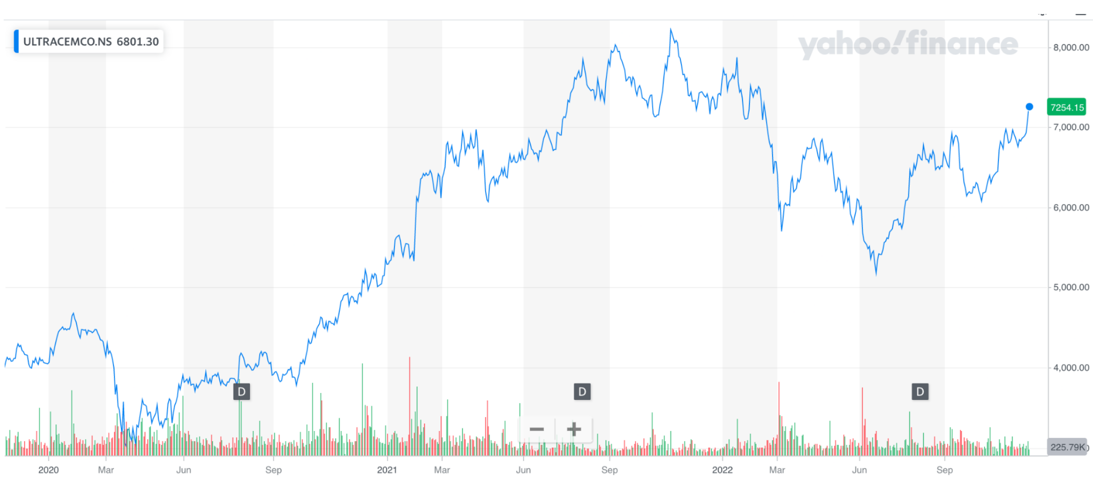
Estimation of Beta Using CAPM Model

The CAPM model can be described as
E(R) = Rf + Beta * (Rm -Rf)
Where

- E(R) is the expected return of the firm
- Rm is the returns of the market
- Rf is the risk free rate

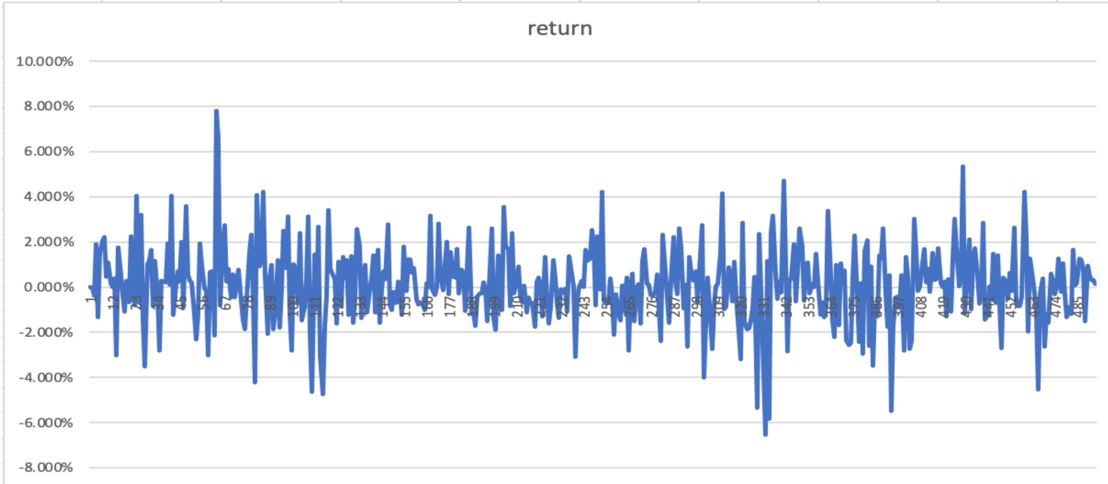
Beta can be estimated by running a regression model where the dependent variable y is the returns of the firm and the independent variable x is the returns of the market. The slope parameter estimated from the regression model is the beta of the CAPM model. Beta of a security tells us how sensitive the security's returns are to the market's returns.

Returns were calculated for a daily basis from November 1st 2020 to 30st 2022 (2 years). The closing prices of the security is plotted in the graph shown below. The excess returns were calculated for the security as well as the index.



Daily Closing Prices for Ultratech cement

The returns of the security was calculated for the analysis period and the plot is shown in the figure below. Return distribution was a random walk and the returns oscillated between -10% to 10%.. There were some outliers present in between, where returns were -20% (End of April 2020) and 18% (December 2020).



Daily returns of Ultratech Cement

A linear regression was done between the excess security returns as the dependent variable and excess market returns as the independent variable and the following results were obtained:

```
> regression <- lm(ULTRACEMCO.NS.Close ~ NSEI.Close, data.frame(Returns[]))
> summary(regression)

Call:
lm(formula = ULTRACEMCO.NS.Close ~ NSEI.Close, data = data.frame(Returns[]))

Residuals:
      Min        1Q    Median        3Q       Max
-0.059670 -0.008331 -0.001720  0.007650  0.057363

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0002360  0.0006678   0.353    0.724
NSEI.Close  0.9213191  0.0543604  16.948   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01471 on 491 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.3691,	Adjusted R-squared:  0.3678
F-statistic: 287.2 on 1 and 491 DF,  p-value: < 2.2e-16
```

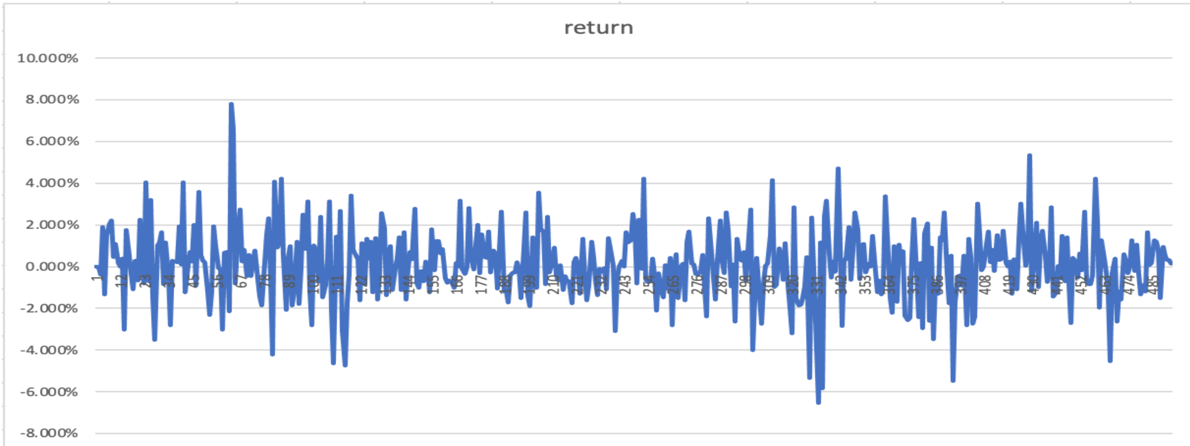
Regression statistics for Ultratech cement And NSEI

Slope of the regression was found to be 0.92 and intercept to be 0.00023. The p value of the slope is less than 0.01, which tells us that the slope of the regression is significant on a 99% Confidence Interval.

Inference: The beta of the stock is 0.92. This tells us that the security's price is less volatile than the market as market beta is considered as 1. Security is less sensitive to macroeconomic factors than the market. If the market moves up by 1%, then this security will move up by only 0.92%.

Estimating AR and MA Coefficients using ARIMA model.

The AR and MA coefficients can be determined by running the ACF and PACF plots.



Daily returns of Ultratech cement

Mean and Variance of the returns were calculated. The mean was 0.00087 and variance was 0.0002. Since the mean is close to zero and variance seems constant throughout the analysis period, we ran an Augmented Dickey- Fuller test to check whether the series is stationary series or not. Results of the test are shown below:

```
> stationary.test(Returns_ULT, method = "pp")
Phillips-Perron Unit Root Test
alternative: stationary

Type 1: no drift no trend
 lag Z_rho p.value
   5  -513    0.01
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   5  -511    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   5  -509    0.01
---------------
Note: p-value = 0.01 means p.value <= 0.01
```

Augmented Dickey-Fuller Test for Ultratech cement Daily returns

The p value of this test is less than 0.05 which tells us to reject the null hypothesis.Therefore, for the Augmented Dickey-Fuller test, we can say that this series is a stationary series. The series is stationary, so it will satisfy the following properties:

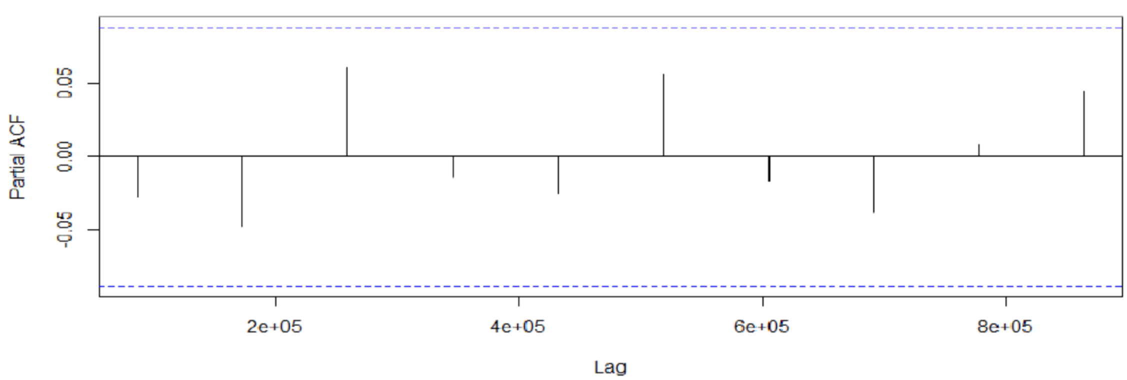
- The mean E(y) is the same for all t.
- The variance of y is the same for all t
- The covariance and correlation between y and y $_{-1}$ is same for all t

ACF Plot

ACF Plot for Daily Returns of ultratech cement Bank

The ACF property defines a well defined pattern for autocorrelation. From our graph, we can see that there is no significant spike. There is one spike at lag order 8, therefore we can say that the order of the MA model is zero. It is estimated as a MA (0) model.

PACF Plot



PACF Plot for Daily Returns of Ultratech cement

Number of spikes in the PACF indicate the suitable AR order.In PACF plot, the number of spikes is not clear(does not show clear pattern) indicating that the AR model order is also 0.

$$\frac{\text{Covariance}(x_t, x_{t-3} \mid x_{t-1}, x_{t-2})}{\sqrt{\text{Variance}(x_t \mid x_{t-1}, x_{t-2})\text{Variance}(x_{t-3} \mid x_{t-1}, x_{t-2})}}$$

After this, we run the ARIMA test on all orders (p,d,q) which we might think would make a good model. The best model is the one with the lowest AIC score. Using the ARIMA model then we predict values for a small interval of time and evaluate the model

Identification and interpretation of ARIMA model

ARIMA models may include all or none of the autoregressive terms, moving average terms, and differencing parameters.

When no differencing is required the models can be expressed as ARIMA(p,0,q) type. In cases where the data are non-stationary, we need to incorporate the differencing factors. So in case of stock price modelling we may very need differencing but as returns are already a relative difference we are not likely to encounter differencing for modelling returns.

For daily returns data, from the ACF and PACF plots we have a MA(0) and AR(0) model. We ran the auto.arima() function to cross examine our results. The results we obtained from the auto.arima() function was that the model is AR(0) and MA(0) model.

Thus, the values that have been used for both p and q is zero.

```
> fit1 <- auto.arima(Returns_ULT$Returns , ic = "bic")
> summary(fit1)
Series: Returns_ULT$Returns
ARIMA(0,0,0) with zero mean

sigma^2 = 0.0003429:  log likelihood = 1272.23
AIC=-2542.45   AICc=-2542.45   BIC=-2538.25

Training set error measures:
                      ME       RMSE        MAE MPE MAPE MASE        ACF1
Training set 0.001684026 0.01851649 0.01350661 100  100    1 -0.02746097
```

Auto ARIMA results for Daily Returns of Ultratech cement

The results for the ARIMA model are presented below

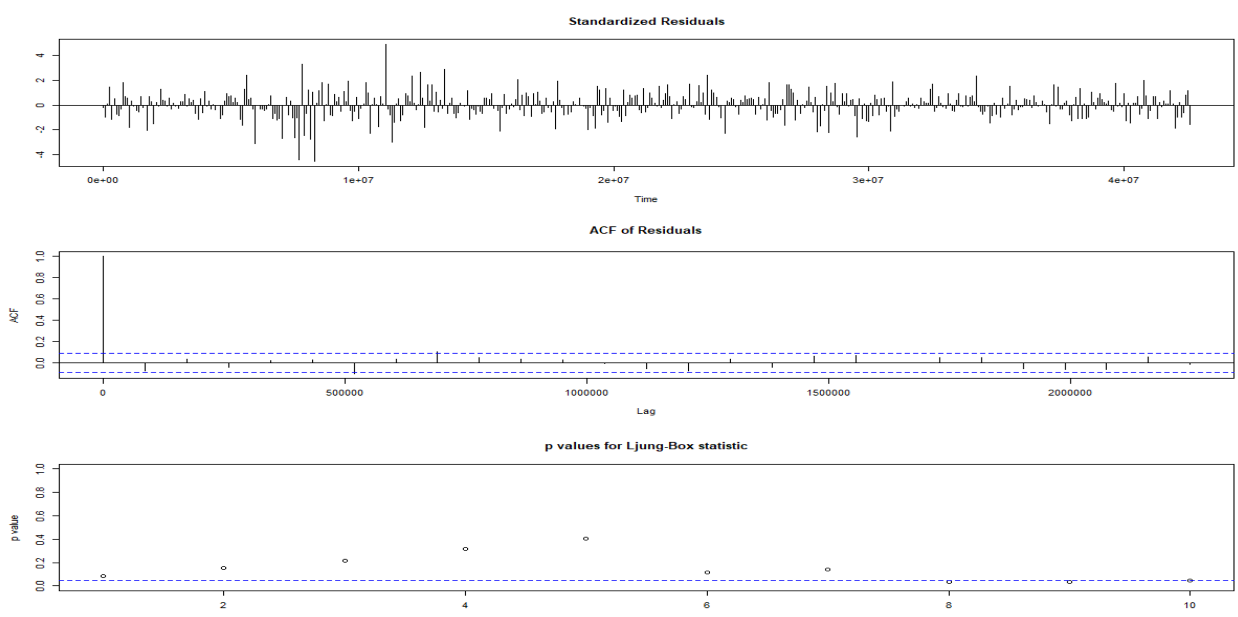
```
> arima_final_ULT <- arima(Returns_ULT$Returns, order = c(2,0,2))
> arima_final_ULT

Call:
arima(x = Returns_ULT$Returns, order = c(2, 0, 2))

Coefficients:
          ar1      ar2     ma1     ma2  intercept
      -0.8588  -0.8120  0.8358  0.7426     0.0017
s.e.   0.1982   0.1341  0.2277  0.1531     0.0008

sigma^2 estimated as 0.0003354:  log likelihood = 1277.62,  aic = -2543.23
```

ARIMA model test for Daily returns of Ultratech cement

The AIC value is - 2543.23.

The BIC value is - 2538.25

Diagnostic Test



Diagnostic Model Test for Daily Returns of Ultratech cement

Interpretation:

Standardized Residuals of the model are randomly distributed.

• ACF of residuals is not significant for any value lag.

• The p-values for Ljung-Box are always greater than 0.05.

Therefore, we can conclude on the basis of the above three observations that the model is a good fit.

Prediction using the ARIMA model

```
> predicted <- predict(arima_final_ULT,n.ahead = 10)
> predicted
$pred
Time Series:
Start = 42768001
End = 43545601
Frequency = 1.15740740740741e-05
 [1] 0.001847690 0.001266544 0.001906898 0.001828885 0.001375907 0.001828251 0.001807619 0.001458030 0.001774995
[10] 0.001786668

$se
Time Series:
Start = 42768001
End = 43545601
Frequency = 1.15740740740741e-05
 [1] 0.01831481 0.01831965 0.01834220 0.01837654 0.01837793 0.01839194 0.01840932 0.01840962 0.01841814 0.01842682
```

Forecasted Returns Of ultratech cement using ARIMA model

This is something specific to a stable series. As already mentioned, historical data can lead to convergent future predictions only for stable data or for smoothened (differenced) data. The prediction interval has been decided by seeing when the forecast converges. This is because after running for some interval, the data series will converge at one value and the curve will stabilize.

Forecasting Volatility using GARCH & EGARCH models

We run the GARCH models again on the daily returns of Ultratech Cement.

```
> ug_spec <- ugarchspec()
> ug_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model            : sGARCH(1,1)
Variance Targeting     : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model             : ARFIMA(1,0,1)
Include Mean           : TRUE
GARCH-in-Mean          : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

Fig 12 GARCH model Specs for Daily Returns of Ultratech cement

From the above table we see that GARCH (1,1) is the most appropriate model and by default the mean model ARFIMA(1,0,1) is chosen.
We run the EGARCH models again on the daily returns of Ultratech cement.

```
> eg_spec <- ugarchspec(variance.model = list(model="eGARCH"))
> eg_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

EGARCH model Specs for Daily Returns of Ultratech cement

From the above table we see that EGARCH (1,1) is the most suitable model and by default the mean model ARFIMA(1,0,1) is chosen. These results are similar to what we observed for the GARCH model.

Estimating the Model

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```
> ugfit <- ugarchfit(spec = ug_spec , data = rULT)
> ugfit

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001666    0.000738  2.25709 0.024003
ar1     0.402025    0.785435  0.51185 0.608756
ma1    -0.425764    0.775936 -0.54871 0.583205
omega   0.000013    0.000001 18.19636 0.000000
alpha1  0.055322    0.007428  7.44790 0.000000
beta1   0.905370    0.013361 67.76135 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001666    0.000781  2.13306  0.03292
ar1     0.402025    0.425846  0.94406  0.34514
ma1    -0.425764    0.420451 -1.01263  0.31123
omega   0.000013    0.000001 12.05826  0.00000
alpha1  0.055322    0.008558  6.46448  0.00000
beta1   0.905370    0.014765 61.31718  0.00000

LogLikelihood : 1291.507
```

```
Information Criteria
------------------------------------

Akaike       -5.1835
Bayes        -5.1326
Shibata      -5.1838
Hannan-Quinn -5.1635

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.003997  0.9496
Lag[2*(p+q)+(p+q)-1][5]  2.395557  0.8307
Lag[4*(p+q)+(p+q)-1][9]  3.279098  0.8439
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.270  0.2597
Lag[2*(p+q)+(p+q)-1][5]     2.447  0.5172
Lag[4*(p+q)+(p+q)-1][9]     3.924  0.6018
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.0376 0.500 2.000  0.8463
ARCH Lag[5]    2.3245 1.440 1.667  0.4039
ARCH Lag[7]    3.2705 2.315 1.543  0.4640
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  21.0952
Individual Statistics:
mu     0.33194
ar1    0.23402
ma1    0.24939
omega  1.57341
alpha1 0.08309
beta1  0.11016

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           0.8104 0.4181
Negative Sign Bias  0.7461 0.4560
Positive Sign Bias  0.5957 0.5517
Joint Effect        2.5857 0.4600


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     39.56     0.003731
2    30     42.19     0.054039
3    40     56.74     0.032952
4    50     61.06     0.115771


Elapsed time : 0.1522
```

Diagnostic Test of GARCH model for Daily Returns of Ultratech cement

Interpretation:

- In GARCH, the variance tends to show mean reversion which means it gets pulled to a long-term volatility rate over time.
- The conclusion obtained from the weighted Ljung-Box Test shows us that there is no relationship between the residuals and this is a stable model.
- Here Omega, Alpha and Beta are obtained from estimated standard errors in the figure above.

GARCH Model Forecasting

We use the GARCH model for predicting volatility. Results are shown in the figure given below

```
> ugforecast2 = ugarchforecast(ugfit2, n.ahead=10)
> ugforecast2

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2021-10-28]:
         Series   Sigma
T+1   0.0044208 0.02462
T+2  -0.0006067 0.02464
T+3   0.0020359 0.02466
T+4   0.0006468 0.02467
T+5   0.0013770 0.02469
T+6   0.0009932 0.02471
T+7   0.0011949 0.02472
T+8   0.0010889 0.02474
T+9   0.0011446 0.02475
T+10  0.0011153 0.02476
```

GARCH Model Volatility Forecast for Daily Returns of Ultratech cement

WEEKLY RETURNS

Estimation of Beta Using CAPM Model

The CAPM model can be described as
E(R) = Rf + Beta * (Rm -Rf)
Where

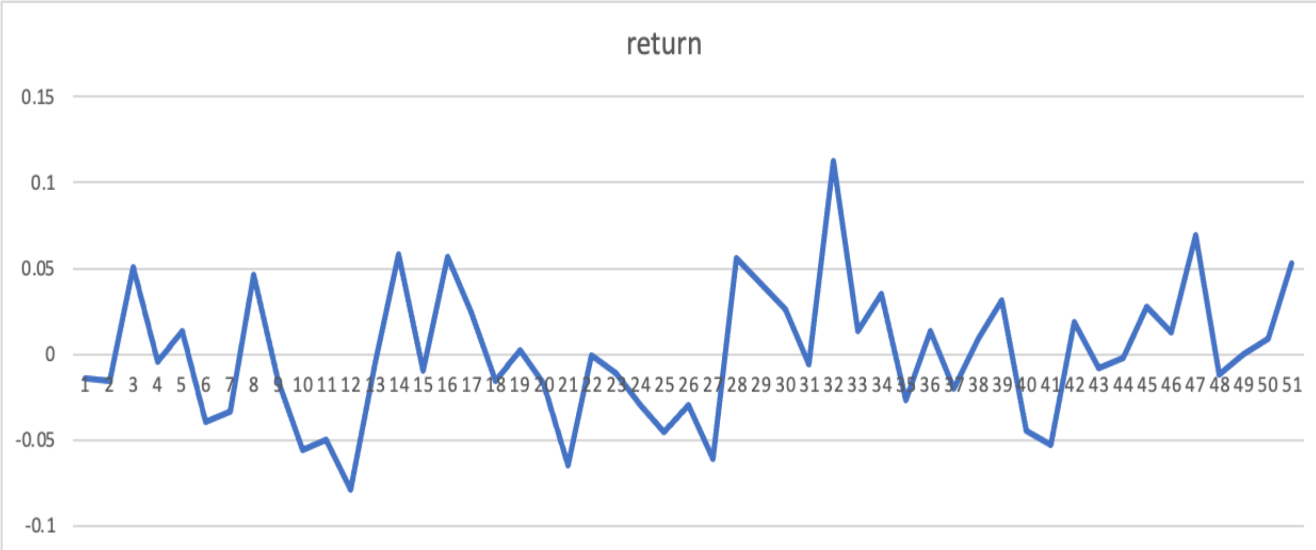
- E(R) is the expected return of the firm
- Rm is the returns of the market
- Rf is the risk free rate

Beta can be estimated by running a regression model where the dependent variable y is the returns of the firm and the independent variable x is the returns of the market. The slope parameter estimated from the regression model is the beta of the CAPM model. Beta of a security tells us how sensitive the security's returns are to the market's returns.

Returns were calculated for a daily basis from 1st Nov 2020 to 31th Oct 2022. The closing prices of the security is plotted in the graph shown below. The excess returns were calculated for the security as well as the index.

Weekly Closing Prices of ultratech cement

The returns of the security was calculated for the analysis period and the plot is shown in the figure below.



Weekly Returns of ultratech cement

A linear regression was performed between the excess security returns as the dependent variable and excess market returns as the independent variable and the following results were obtained:

```
> regression <- lm(ULTRACEMCO.NS.Close ~ NSEI.Close, data.frame(Returns[]))
> summary(regression)

Call:
lm(formula = ULTRACEMCO.NS.Close ~ NSEI.Close, data = data.frame(Returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.079239 -0.020756 -0.005683  0.020186  0.101115 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.0009137  0.0034735   0.263    0.793    
NSEI.Close  0.9552111  0.1200426   7.957 2.53e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03411 on 102 degrees of freedom
Multiple R-squared:  0.383,	Adjusted R-squared:  0.377 
F-statistic: 63.32 on 1 and 102 DF,  p-value: 2.528e-12
```

Regression statistics for ultratech cement And NSEI

Slope of the regression was found to be 0.955 and intercept to be 0.00091. The p value of the slope is less than 0.01, which tells us that the slope of the regression is significant on a 99% Confidence Interval.

Inference: The beta of the stock is 0.955. This tells us that the security's price is less volatile than the market. Security is less sensitive to macroeconomic factors than the market. If the market moves up/down by 1%, then this security will move up/down by 0.955%.

Estimating AR and MA Coefficients using ARIMA model.

The AR and MA coefficients can be determined by running the ACF and PACF plots. . Since the mean is close to zero and variance seems constant throughout the analysis period, we ran an Augmented Dickey- Fuller test to check whether the series is stationary series or not. Results of the test are shown below:

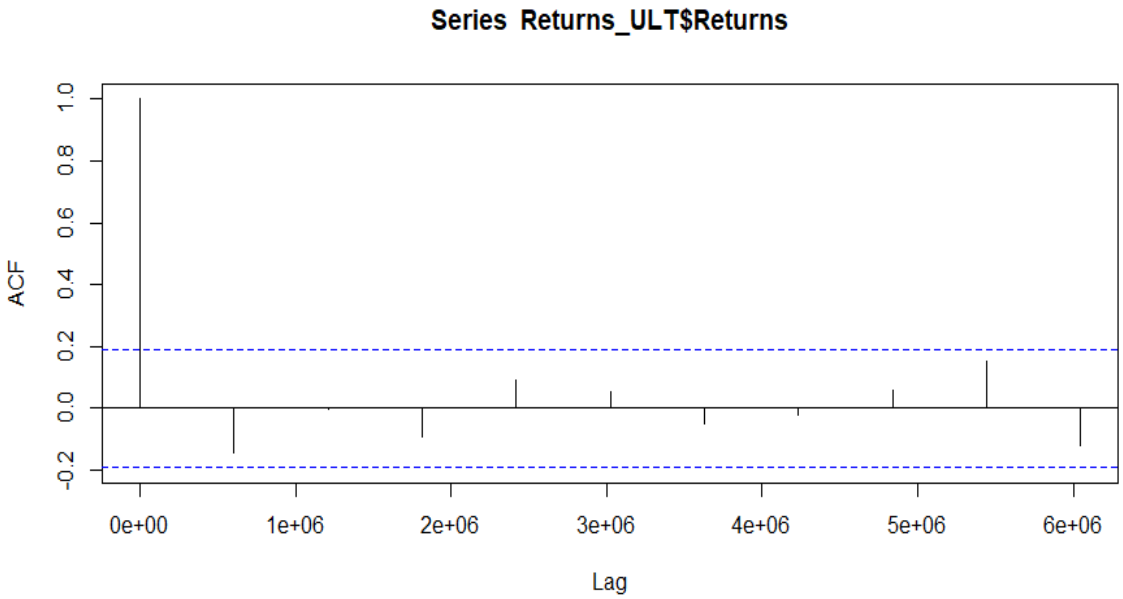
```
> stationary.test(Returns_ULT, method = "pp")
Phillips-Perron Unit Root Test
alternative: stationary

Type 1: no drift no trend
 lag Z_rho p.value
   4  -114    0.01
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   4  -113    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   4  -111    0.01
---------------
Note: p-value = 0.01 means p.value <= 0.01
```

Results of ADF Test for Weekly Returns of ultratech cement

The p value of this test is greater than 0.05 which tells us that we fail to reject the null hypothesis. The series is non-stationary.

Since the series is found to be non stationary, therefore it will not follow the below properties:
- The mean E(y) is the same for all t.
- The variance of y is the same for all t
- The covariance and correlation between y and y_{-1} is same for all t

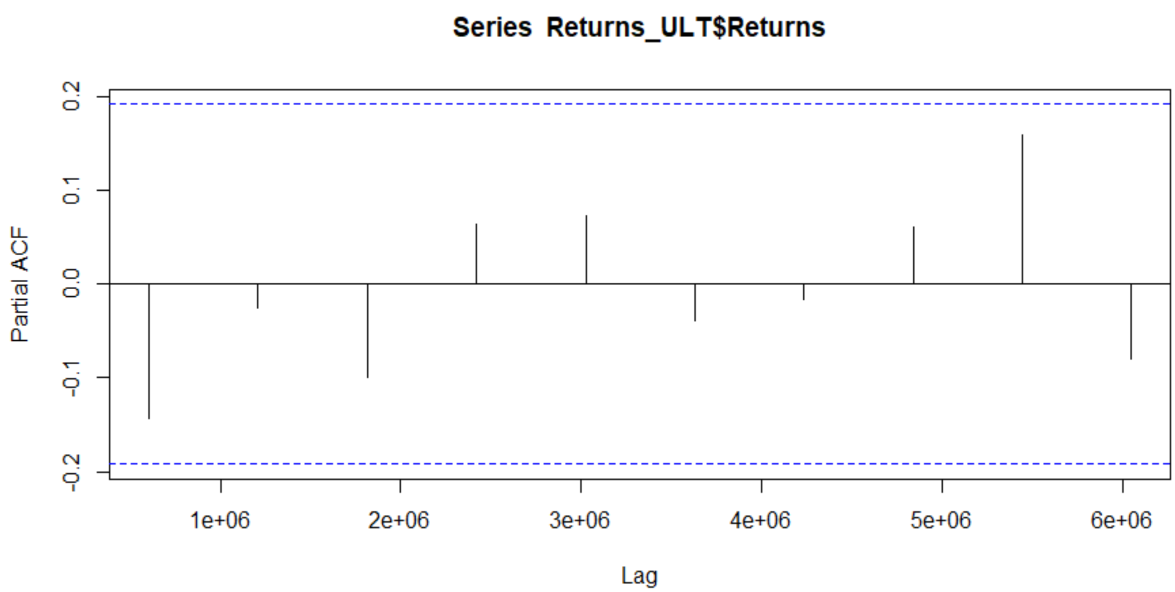
ACF Plot



ACF Plot for Weekly Returns of ultratech cement

The ACF property defines a distinct pattern for the autocorrelations.Since, the ACF is not significant for any value of lag, the order of the moving average model is zero. It is estimated to be a MA (0) model.

PACF Plot



PACF Plots for Weekly Returns of ultratech cement

Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero. After this, we run the ARIMA model on all orders (p,d,q) which we think might make a good model and choose the best amongst them. The best model is that which has the least AIC value. Using the ARIMA model then we predict values for a small interval of time and evaluate the model.

Identification and interpretation of ARIMA model

ARIMA models may include all or none of the autoregressive terms, moving average terms, and differencing parameters.

When no differencing is required the models can be expressed as ARIMA(p,0,q) type. In cases where the data are non-stationary, we need to incorporate the differencing factors. So in case of stock price modelling we may very need differencing but as returns are already a relative difference we are not likely to encounter differencing for modelling returns.

For weekly returns data, from the ACF and PACF plots we have a MA(0) and AR(0) model. We ran the auto.arima() function to cross examine our results. The results we obtained from the auto.arima() function was that the model is AR(0) and MA(0) model.

Thus, the values that have been used for both p and q is zero.

```
> fit <- auto.arima(Returns_ULT$Returns)
> summary(fit)
Series: Returns_ULT$Returns
ARIMA(3,1,1)

Coefficients:
          ar1      ar2      ar3      ma1
      -0.2126  -0.1094  -0.1674  -0.9365
s.e.   0.1052   0.1079   0.1073   0.0400

sigma^2 = 0.001858:  log likelihood = 178.26
AIC=-346.51   AICc=-345.9   BIC=-333.34

Training set error measures:
                       ME       RMSE        MAE      MPE     MAPE     MASE         ACF1
Training set -0.007378439 0.04205726 0.03275624 105.8191 179.8816 1.007811 -0.006258164
```

Auto ARIMA results for Weekly Returns of ultratech cement

The results for the ARIMA model are presented below

```
> arima_final2 <- arima(returns_rec, order= c(0,0,0))
> arima_final2

Call:
arima(x = returns_rec, order = c(0, 0, 0))

Coefficients:
      intercept
         0.0019
s.e.     0.0053

sigma^2 estimated as 0.002902:  log likelihood = 156.24,  aic = -308.47
```

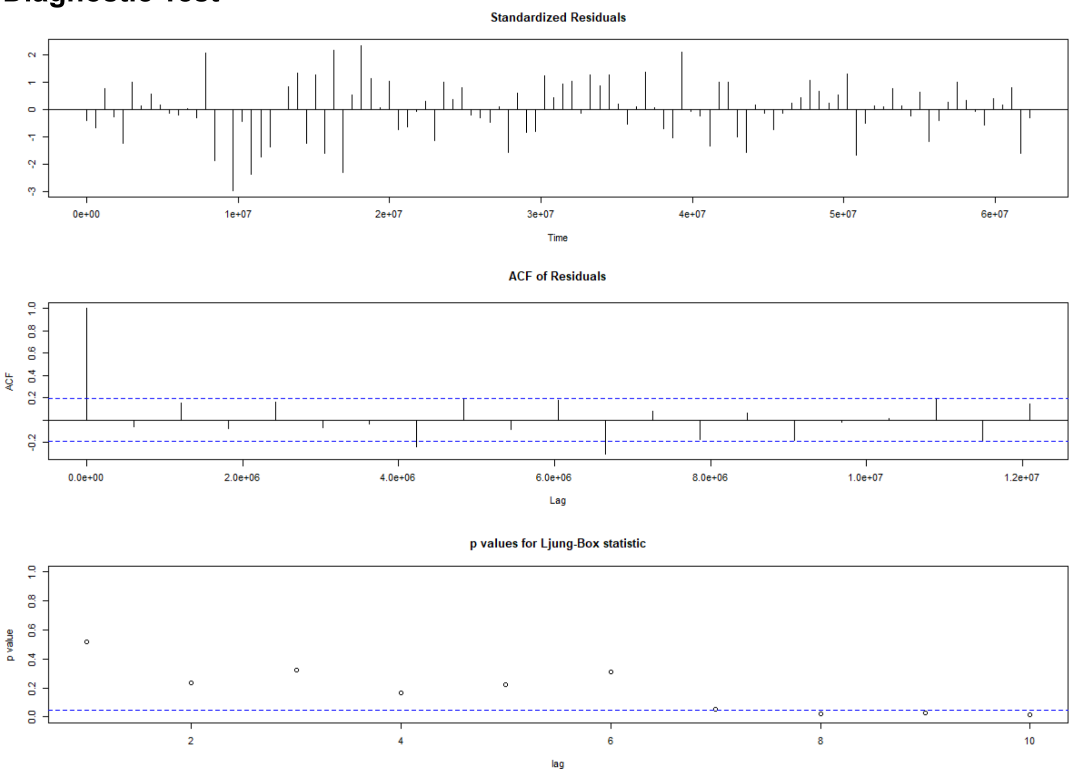
ARIMA model Test for Weekly returns of ultratech cement

We do not have any coefficients.

The AIC value is -346.51.

The BIC value is -333.34

Diagnostic Test



Diagnostic Test for Weekly returns of ultratech cement

Interpretation:

• Standardized Residuals of the model are randomly distributed.
• ACF of residuals is not significant for any value lag.
• The p-values for Ljung-Box is greater than 0.05 for first 2 lags

Therefore, we can conclude on the basis of above three observations that the model is a moderate fit.

Prediction using the ARIMA model

```
> predicted <- predict(arima_final_ULT,n.ahead = 10)
> predicted
$pred
Time Series:
Start = c(62899201, 1)
End = c(68342401, 1)
Frequency = 1.65343915343915e-06
 [1] -0.0246187573 -0.0042968137 -0.0101824430  0.0006448338 -0.0044142826 -0.0035382623 -0.0049832823 -0.0039251587
 [9] -0.0041386216 -0.0039671376

$se
Time Series:
Start = c(62899201, 1)
End = c(68342401, 1)
Frequency = 1.65343915343915e-06
 [1] 0.04226093 0.04272770 0.04273191 0.04288098 0.04312317 0.04317955 0.04324154 0.04325784 0.04329569 0.04333238
```

ARIMA model Forecast for Weekly Returns of ultratech cement

This is something specific to a stable series. As already mentioned, historical data can lead to convergent future predictions only for stable data or for smoothened (differenced) data. The prediction interval has been decided by seeing when the forecast converges. This is because after running for some interval, the data series will converge at one value and the curve will stabilize

The ARIMA Model was used to predict the return after the analysis period. The forecast given by the model is given above.

Forecasting Volatility using GARCH & EGARCH models

We run the GARCH models again on the daily returns of ultratech cement.

```
> ug_spec <- ugarchspec()
> ug_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : sGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

GARCH Model Specs for Weekly Returns of ultratech cement

From the above table we see that GARCH (1,1) is the most appropriate model and by default the mean model ARFIMA(1,0,1) is chosen.

We run the EGARCH models again on the daily returns of ultratech cement.

```
> eg_spec <- ugarchspec(variance.model = list(model="eGARCH"))
> eg_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

EGARCH Model Specs for Weekly Returns of ultratech cement

From the above table we see that EGARCH (1,1) is the most suitable model and by default the mean model ARFIMA(1,0,1) is chosen. These results are similar to what we observed for the GARCH model.

Estimating the Model

```
> ugfit <- ugarchfit(spec = ug_spec , data = rULT)
> ugfit

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.007429    0.003311   2.24374 0.024849
ar1     0.178016    0.432276   0.41181 0.680478
ma1    -0.355640    0.406068  -0.87581 0.381132
omega   0.000006    0.000003   2.36985 0.017795
alpha1  0.000000    0.006961   0.00000 1.000000
beta1   0.995366    0.002068 481.28944 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.007429    0.003784   1.96312 0.049632
ar1     0.178016    0.267149   0.66635 0.505185
ma1    -0.355640    0.232658  -1.52859 0.126365
omega   0.000006    0.000002   2.97073 0.002971
alpha1  0.000000    0.002890   0.00000 1.000000
beta1   0.995366    0.003372 295.16058 0.000000

LogLikelihood : 182.541
```

```
Information Criteria
------------------------------------

Akaike       -3.3627
Bayes        -3.2110
Shibata      -3.3688
Hannan-Quinn -3.3012

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                  1.386e-05  0.9970
Lag[2*(p+q)+(p+q)-1][5] 5.189e-01  1.0000
Lag[4*(p+q)+(p+q)-1][9] 1.529e+00  0.9967
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.08974  0.7645
Lag[2*(p+q)+(p+q)-1][5]   2.74510  0.4556
Lag[4*(p+q)+(p+q)-1][9]   4.84854  0.4520
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.3213 0.500 2.000  0.5708
ARCH Lag[5]    4.6499 1.440 1.667  0.1237
ARCH Lag[7]    5.4150 2.315 1.543  0.1858
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  7.1993
Individual Statistics:
mu     0.55901
ar1    0.75091
ma1    0.70994
omega  0.09514
alpha1 0.11393
beta1  0.08744

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          0.007332 0.99416
Negative Sign Bias 2.276924 0.02492  **
Positive Sign Bias 0.001282 0.99898
Joint Effect       9.003062 0.02925  **


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20      7.19       0.9931
2    30     17.00       0.9622
3    40     30.24       0.8416
4    50     43.10       0.7103


Elapsed time : 0.1058481
```

Diagnostic Test of GARCH Model for Weekly Returns of ultratech cement

Interpretation:

- In GARCH, the variance tends to show mean reversion which means it gets pulled to a long-term volatility rate over time.
- The conclusion obtained from the weighted Ljung-Box Test shows us that there is no relationship between the residuals and this is a stable model.
- Here Omega, Alpha and Beta are obtained from estimated standard errors in the figure above.

GARCH Model Forecast:

Now we use the GARCH Model to forecast volatility. The forecast are as follows:

```
> ugforecast <- ugarchforecast(ugfit, n.ahead = 10)
> ugforecast

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: sGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2022-03-28]:
        Series   Sigma
T+1  0.0009507 0.04009
T+2  0.0062756 0.04007
T+3  0.0072235 0.04005
T+4  0.0073923 0.04004
T+5  0.0074223 0.04002
T+6  0.0074277 0.04000
T+7  0.0074286 0.03998
T+8  0.0074288 0.03996
T+9  0.0074288 0.03994
T+10 0.0074288 0.03992
```

GARCH Model Volatility Forecast for Weekly Returns of ultratech cement

MONTHLY RETURNS

Estimation of Beta Using CAPM Model

The CAPM model can be described as
E(R) = Rf + Beta * (Rm -Rf)
Where

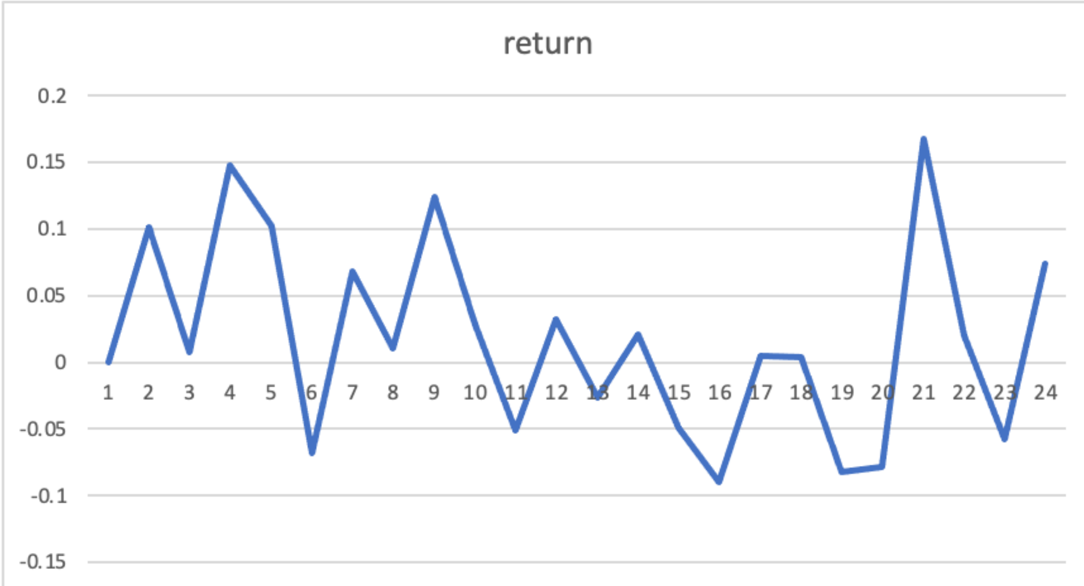
- E(R) is the expected return of the firm
- Rm is the returns of the market
- Rf is the risk free rate

Beta can be estimated by running a regression model where the dependent variable y is the returns of the firm and the independent variable x is the returns of the market. The slope parameter estimated from the regression model is the beta of the CAPM model. Beta of a security tells us how sensitive the security's returns are to the market's returns.

Returns were calculated for a monthly basis from 1st nov 2020 to 31st oct 2022. The closing prices of the security is plotted in the graph shown below. The excess returns were calculated for the security as well as the index.

Monthly Closing Prices of ultratech cement

The returns of the security was calculated for the analysis period and the plot is shown in the figure below.



Monthly Returns for ultratech cement

A linear regression was performed between the excess security returns as the dependent variable and excess market returns as the independent variable and the following results were obtained:

```
> regression <- lm(ULTRACEMCO.NS.Close ~ NSEI.Close, data.frame(Returns[]))
> summary(regression)

Call:
lm(formula = ULTRACEMCO.NS.Close ~ NSEI.Close, data = data.frame(Returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.089643 -0.045797 -0.006355  0.036009  0.106908 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.01616    0.01613   1.001    0.328
NSEI.Close   0.52019    0.32794   1.586    0.128

Residual standard error: 0.06568 on 21 degrees of freedom
Multiple R-squared:  0.107,	Adjusted R-squared:  0.06447 
F-statistic: 2.516 on 1 and 21 DF,  p-value: 0.1276
```

Regression statistics for Monthly Returns of ultratech cement and NSEI

Slope of the regression was found to be 0.52 and intercept to be 0.016. The p value of the slope is less than 0.01, which tells us that the slope of the regression is significant on a 99% Confidence Interval.

Inference: The beta of the stock is 0.52. This tells us that the security's price is less volatile than the market. Security is less sensitive to macroeconomic factors than the market. If the market moves up/down by 1%, then this security will move up/down by 0.52%.

Estimating AR and MA Coefficients using ARIMA model.

The AR and MA coefficients can be determined by running the ACF and PACF plots.

Since the mean is close to zero and variance seems constant throughout the analysis period, we ran an Augmented Dickey- Fuller test to check whether the series is stationary series or not. Results of the test are shown below:

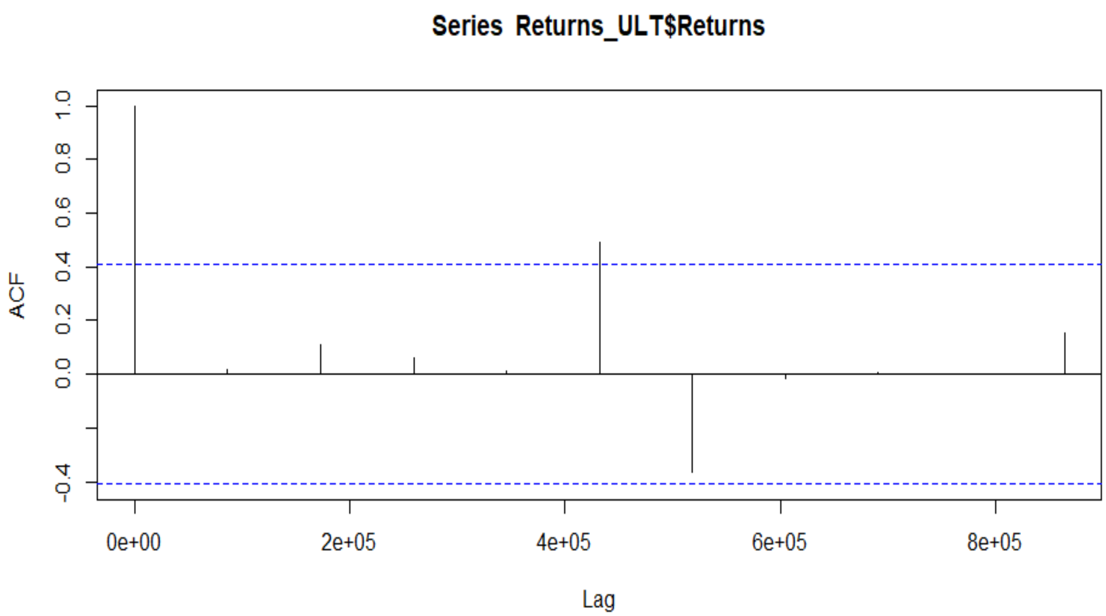
```
> stationary.test(Returns_ULT, method = "pp")
Phillips-Perron Unit Root Test
alternative: stationary

Type 1: no drift no trend
 lag Z_rho p.value
   2 -19.3    0.01
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   2 -22.6    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   2 -25.4    0.01
---------------
Note: p-value = 0.01 means p.value <= 0.01
```

Augmented Dickey-Fuller Test for Monthly returns of ultratech cement

The p value of this test is greater than 0.05 which tells us that we fail to reject the null hypothesis. The series is non-stationary.

Since the series is found to be non stationary, therefore it will not follow the below properties:
- The mean E(y) is the same for all t.
- The variance of y is the same for all t
- The covariance and correlation between y and y $_{-1}$ is same for all t

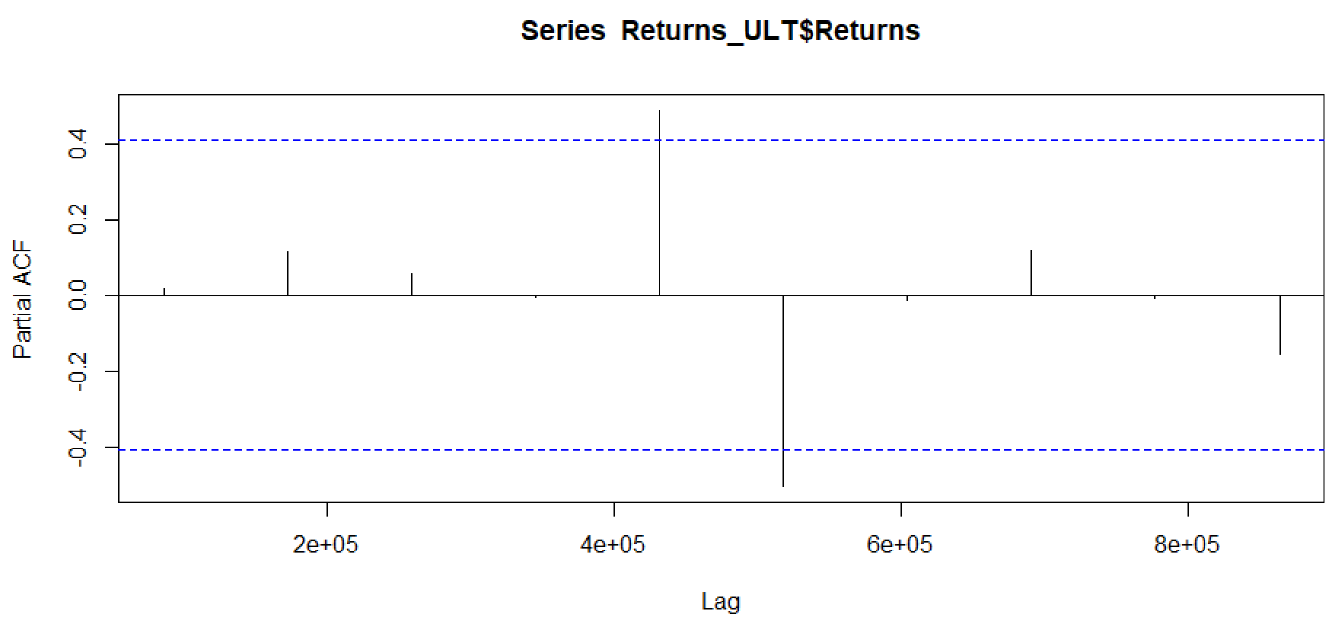
ACF Plot



ACF Plot for Monthly Returns of ultratech cement

The ACF property defines a distinct pattern for the autocorrelations.Since, the ACF is not significant for any value of lag, the order of the moving average model is zero. It is estimated to be a MA (0) model.

PACF Plot



PACF Plot for Monthly Returns of ultratech cement

Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero.

After this, we run the ARIMA model on all orders (p,d,q) which we think might make a good model and choose the best amongst them. The best model is that which has the least AIC value.

Using the ARIMA model then we predict values for a small interval of time and evaluate the model.

Identification and interpretation of ARIMA model

ARIMA models may include all or none of the autoregressive terms, moving average terms, and differencing parameters.

When no differencing is required the models can be expressed as ARIMA(p,0,q) type. In cases where the data are non-stationary, we need to incorporate the differencing factors. So in case of stock price modeling we may very need differencing but as returns are already a relative difference we are not likely to encounter differencing for modeling returns.

For monthly returns data, from the ACF and PACF plots we have a MA(0) and AR(0) model. We ran the auto.arima() function to cross examine our results. The results we obtained from the auto.arima() function was that the model is AR(0) and MA(0) model.

Thus, the values that have been used for both p and q is zero.

```
> fit <- auto.arima(Returns_ULT$Returns)
> summary(fit)
Series: Returns_ULT$Returns
ARIMA(0,1,1)

Coefficients:
          ma1
      -0.7980
s.e.   0.1332

sigma^2 = 0.004929:  log likelihood = 27.23
AIC=-50.46   AICc=-49.82   BIC=-48.27

Training set error measures:
                      ME       RMSE        MAE     MPE   MAPE      MASE       ACF1
Training set -0.01557815 0.06708291 0.05273882 150.848 258.97 0.8845035 -0.1920383
>
```

Auto ARIMA results for Monthly Returns of ultratech cement

```
> fit <- auto.arima(Returns_ULT$Returns)
> summary(fit)
Series: Returns_ULT$Returns
ARIMA(0,1,1)

Coefficients:
          ma1
      -0.7980
s.e.   0.1332

sigma^2 = 0.004929:  log likelihood = 27.23
AIC=-50.46   AICc=-49.82   BIC=-48.27

Training set error measures:
                      ME       RMSE        MAE     MPE   MAPE      MASE       ACF1
Training set -0.01557815 0.06708291 0.05273882 150.848 258.97 0.8845035 -0.1920383
>
```

ARIMA model Test for Monthly returns of ultratech cement

We do not have any coefficients.

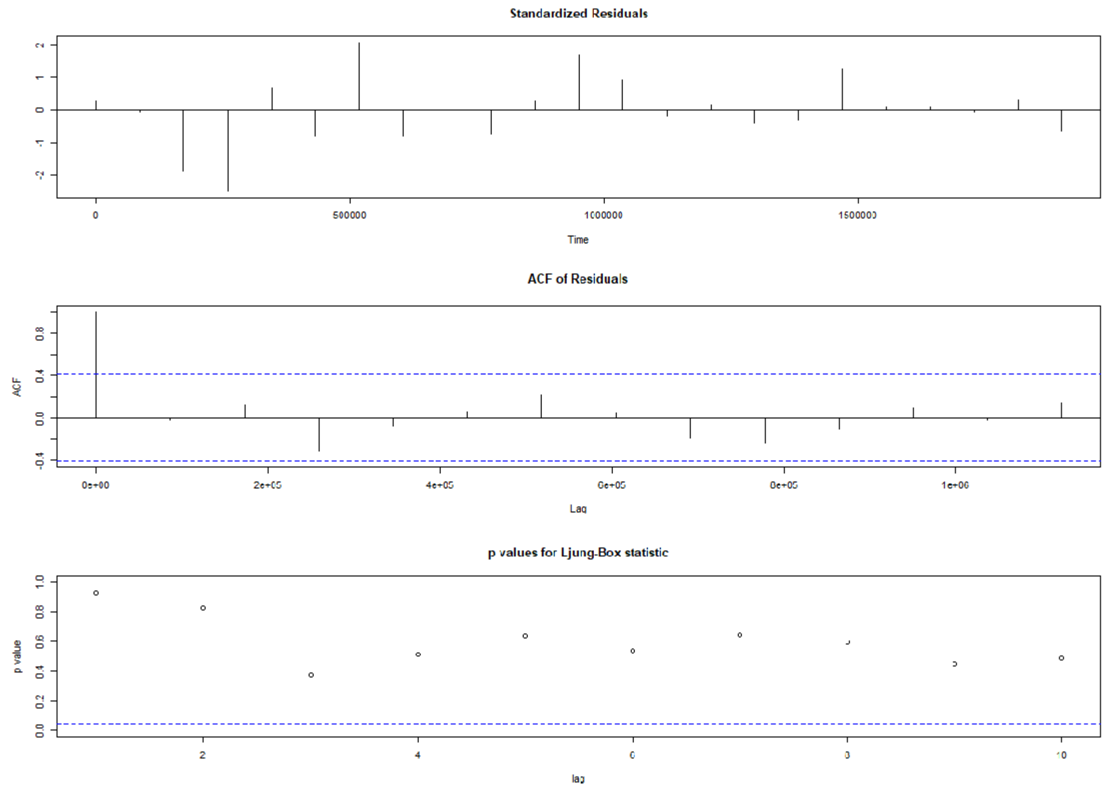
The AIC value is -50.46.

The BIC value is -48.27.

ESTIMATED COEFFICIENT - ARIMA MODEL

```
> arima_final2 <- arima(returns_rec, order= c(0,0,0))
> arima_final2

Call:
arima(x = returns_rec, order = c(0, 0, 0))

Coefficients:
      intercept
         0.0086
s.e.     0.0212

sigma^2 estimated as 0.01036:  log likelihood = 19.92,  aic = -35.84
```

Diagnostic Test



Diagnostic Test for Monthly Returns of Ultratech cement

Interpretation:
• Standardized Residuals of the model are randomly distributed.
• ACF of residuals is not significant for any value lag.
• The p-values for Ljung-Box is greater than 0.05
Therefore, we can conclude on the basis of above three observations that the model is a moderate fit.

Prediction using the ARIMA model

```
> predicted <- predict(arima_final_ULT,n.ahead = 10)
> predicted
$pred
Time Series:
Start = 1987201
End = 2764801
Frequency = 1.15740740740741e-05
 [1] -0.009614257 -0.009614257 -0.009614257 -0.009614257 -0.009614257 -0.009614257 -0.009614257 -0.009614257
 [9] -0.009614257 -0.009614257

$se
Time Series:
Start = 1987201
End = 2764801
Frequency = 1.15740740740741e-05
 [1] 0.06859097 0.06997602 0.07133419 0.07266698 0.07397575 0.07526178 0.07652619 0.07777005 0.07899433
[10] 0.08019992
```

ARIMA Model Forecast for Monthly Returns of ultratech cement

This is something specific to a stable series. As already mentioned, historical data can lead to convergent future predictions only for stable data or for smoothened (differenced) data. The prediction interval has been decided by seeing when the forecast converges. This is because after running for some interval, the data series will converge at one value and the curve will stabilize

The forecast given by the model is given above.

Forecasting Volatility using GARCH & EGARCH models

We run the GARCH models again on the daily returns of ultratech cement.

```
> ug_spec <- ugarchspec()
> ug_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model            : sGARCH(1,1)
Variance Targeting     : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model             : ARFIMA(1,0,1)
Include Mean           : TRUE
GARCH-in-Mean          : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

GARCH Specs for Monthly returns of ultratech cement

From the above table we see that GARCH (1,1) is the most appropriate model and by default the mean model ARFIMA(1,0,1) is chosen.
We run the EGARCH models again on the daily returns of ultratech cement.

```
> eg_spec <- ugarchspec(variance.model = list(model="eGARCH"))
> eg_spec

*---------------------------------*
*       GARCH Model Spec          *
*---------------------------------*

Conditional Variance Dynamics
------------------------------------
GARCH Model             : eGARCH(1,1)
Variance Targeting      : FALSE

Conditional Mean Dynamics
------------------------------------
Mean Model              : ARFIMA(1,0,1)
Include Mean            : TRUE
GARCH-in-Mean           : FALSE

Conditional Distribution
------------------------------------
Distribution    :  norm
Includes Skew   :  FALSE
Includes Shape  :  FALSE
Includes Lambda :  FALSE
```

EGARCH Model Specs for Monthly returns for ultratech cement

From the above table we see that EGARCH (1,1) is the most suitable model and by default the mean model ARFIMA(1,0,1) is chosen. These results are similar to what we observed for the GARCH model.

Estimating the Model

```
> ugfit

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

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

Convergence Problem:
Solver Message:
```

```
Information Criteria
------------------------------------

Akaike       -2.1661
Bayes        -1.9207
Shibata      -2.2344
Hannan-Quinn -2.1010

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.6489  0.4205
Lag[2*(p+q)+(p+q)-1][2]    0.6685  0.6195
Lag[4*(p+q)+(p+q)-1][5]    2.2767  0.5546
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.4623  0.4966
Lag[2*(p+q)+(p+q)-1][5]    2.1913  0.5740
Lag[4*(p+q)+(p+q)-1][9]    5.4256  0.3696
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     0.574 0.500 2.000  0.4487
ARCH Lag[5]     3.294 1.440 1.667  0.2499
ARCH Lag[7]     4.346 2.315 1.543  0.2994

Nyblom stability test
------------------------------------
Joint Statistic:  1.4847
Individual Statistics:
mu     0.03823
omega  0.03871
alpha1 0.03868
beta1  0.03876
gamma1 0.03863

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

Diagnostic Test for Monthly Returns of ultratech cement

- In GARCH, the variance tends to show mean reversion which means it gets pulled to a long-term volatility rate over time.
- The conclusion obtained from the weighted Ljung-Box Test shows us that there is no relationship between the residuals and this is a stable model.
- Here Omega, Alpha and Beta are obtained from estimated standard errors in the figure above.

GARCH Model Forecast:

Now we use the GARCH Model to forecast volatility. The forecast are as follows:

```
> ugforecast2 = ugarchforecast(ugfit2, n.ahead=10)
> ugforecast2

*------------------------------------*
*       GARCH Model Forecast         *
*------------------------------------*
Model: eGARCH
Horizon: 10
Roll Steps: 0
Out of Sample: 0

0-roll forecast [T0=2021-10-01]:
       Series   Sigma
T+1  0.009432 0.05040
T+2  0.009432 0.05601
T+3  0.009432 0.06020
T+4  0.009432 0.06323
T+5  0.009432 0.06540
T+6  0.009432 0.06692
T+7  0.009432 0.06797
T+8  0.009432 0.06871
T+9  0.009432 0.06921
T+10 0.009432 0.06956
```

GARCH Model Volatility Forecast for Monthly Returns of ultratech cement

CONCLUSION

Ultratech cement is India’s largest manufacturer of grey cement Ready Mix Concrete (RMC) and white cement.It is also one of the leading cement producers globally .
The results from the company analysis done is given below:

- The beta from regression analysis between security’s returns (dependent variable) and market returns (independent variable) was performed, and beta obtained for different frequencies is given below
    - Daily returns Beta = 0.921
    - Weekly returns Beta = 0.955
    - Monthly returns Beta = 0.52

- ARIMA(0,0,0) model was found to be the best model to forecast returns for all the three frequencies and returns for next 10 time periods were forecasted using the model.

- GARCH(1,1) model was the best fit model to forecast conditional volatility for all the three frequencies and volatility of the next 10 time periods was forecasted using the model.