FRAM ASSIGNMENT

A Financial Study of Indraprastha Gas Ltd, IDFC Bank, IFB Industries and Indian Metals & Ferro Alloys Ltd. in Market Dynamics

Group Number: 25

Instrument Names: IGL, IDFC(merged to IDFCFIRSTB), IFBIND, IMFA

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Acknowledgment

We would like to express our deep gratitude to Prof. Nagaraju Thota AND Prof ACV Subrahmanyam for giving us this valuable opportunity to work under them for the project and also taking out valuable time to provide us the required guidance wherever necessary.Their inputs proved to be very instrumental for the project. We would like to thank them for giving us such a wonderful opportunity to apply our course knowledge on real life data and get a hand on experience. We are greatly indebted for all help throughout the course assignment.

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IGL (Indraprastha Gas Limited)

1.1 About the company

1.1.1. Nature of the business

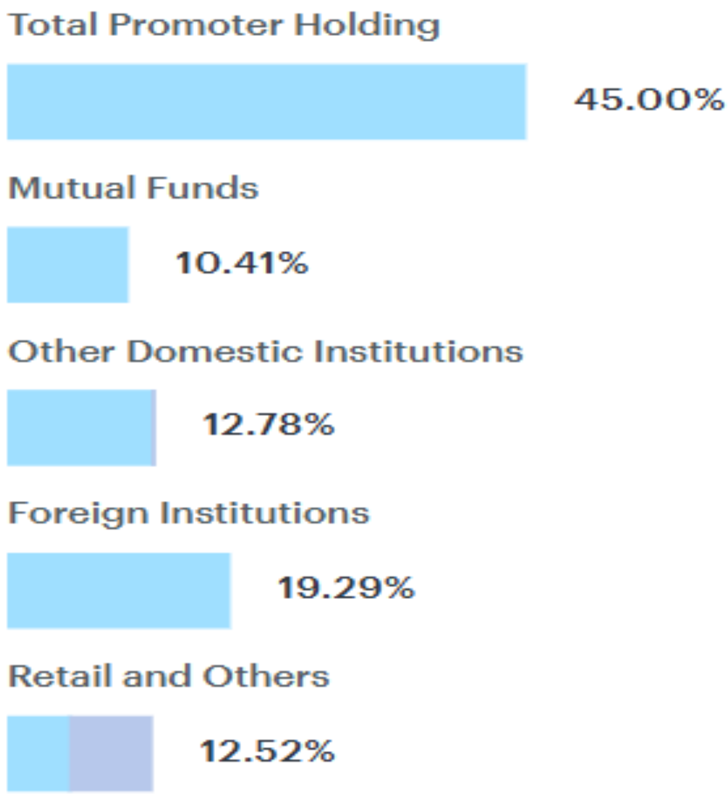
IGL (Indraprastha Gas Limited) is a public sector company despite functioning independently. The company provides natural gas as a cooking and vehicular fuel. It primarily runs operations in Delhi - NCR. It is a distribution based business which provides PNG (Piped Natural Gas) and CNG (Compressed Natural Gas). The company has a wide network of 115 CNG stations catering to about 77,000 vehicles in the region.

1.1.2. Ownership category

A significant chunk of stakes are held by the public sector and the government. GAIL India Limited and BPCL (Bharat Petroleum Corporation Limited) are significant shareholders in IGL. Apart from them, the Government of the National Territory of Delhi also holds some portion of the shares. It is also a publicly listed company on indian stock exchanges NSE and BSE both.

1.1.3. When did it start ?

Indraprastha Gas Limited (IGL) was incorporated in 1998 after it took over Delhi City Gas Distribution Project in 1999 from GAIL. The company was started to cater to fuel demand and control the air pollution in Delhi as a necessary switch to cleaner fuels was highly needed. It began as a joint effort by the government as well as various public sector organizations.



IGL Shareholding pattern

1.14. Overall greatness of the company

IGL plays a pivotal role in staying in accordance with current trends and future expectations and targets that are necessary to be met as a result of climate change. The company is committed to supply CNG and PNG which are fuels of tomorrow. It has also maintained a strong financial performance with consistent growth and profits. It has made major contributions to the environment, people and economy.

1.2 Daily Returns

1.2.1. CAPM Analysis

```
Call:
lm(formula = IGL.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.116572 -0.010231 -0.001049  0.009157  0.110428 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        -0.003530   0.000876  -4.029 6.03e-05 ***
NSEI.ExcessReturns  0.771002   0.052392  14.716  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0185 on 967 degrees of freedom
Multiple R-squared:  0.183,	Adjusted R-squared:  0.1821 
F-statistic: 216.6 on 1 and 967 DF,  p-value: < 2.2e-16
```

Daily Returns Beta = 0.771

Interpretation:

At 0.771, the daily beta of IGL shows the stock is significantly less volatile than the market, which reflects a defensive nature and less sensitivity to daily movements in the market. Being in the business of natural gas distribution for core competencies like IGL is crucial for essential services, thus solidifying this demand, and it is less prone to short-term fluctuations. Low beta for investors means that IGL provides a stable investment option as well, shielding portfolios from excessive volatility while providing steady returns.

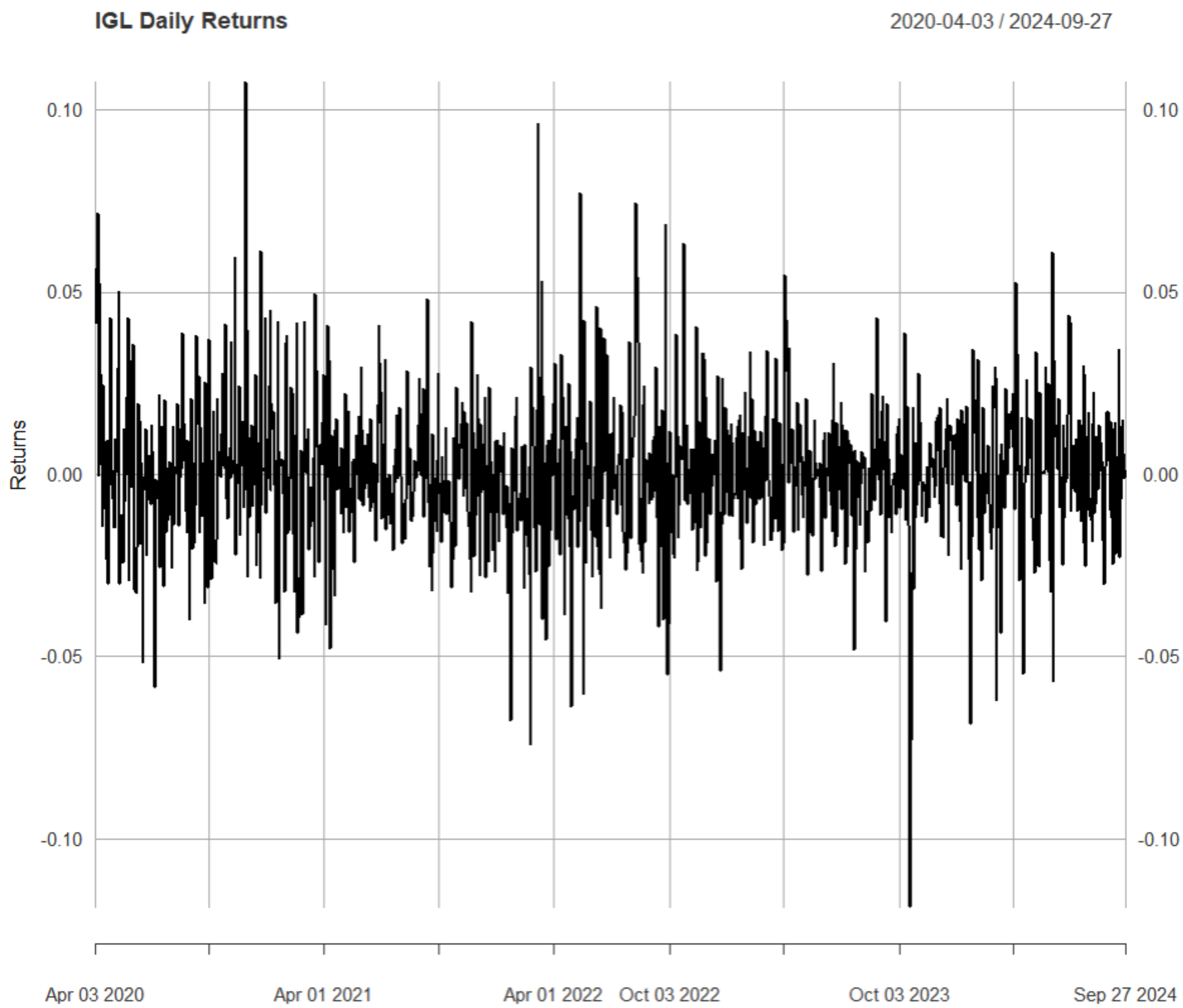


Fig 1 Daily Returns

1.2.2. Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

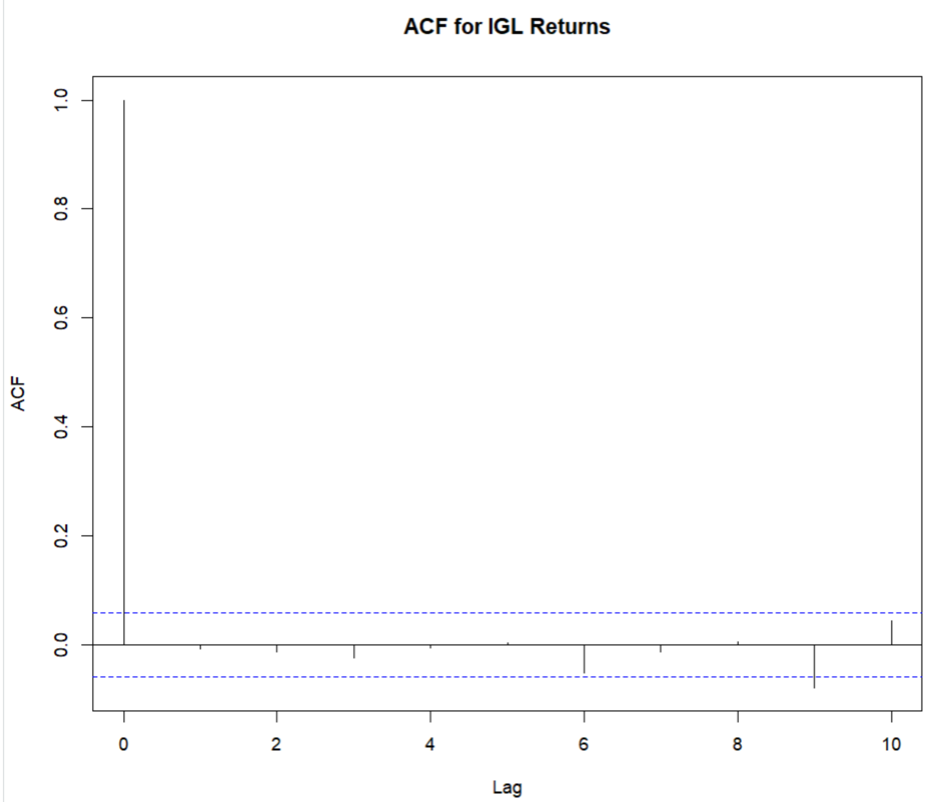
The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots. An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01, which is less than 0.05 or 5%. Hence, the series is


```
        Augmented Dickey-Fuller Test

data:  returns_IGL
Dickey-Fuller = -11.329, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

stationary and rejects the null hypothesis. The experiments yielded the following results:

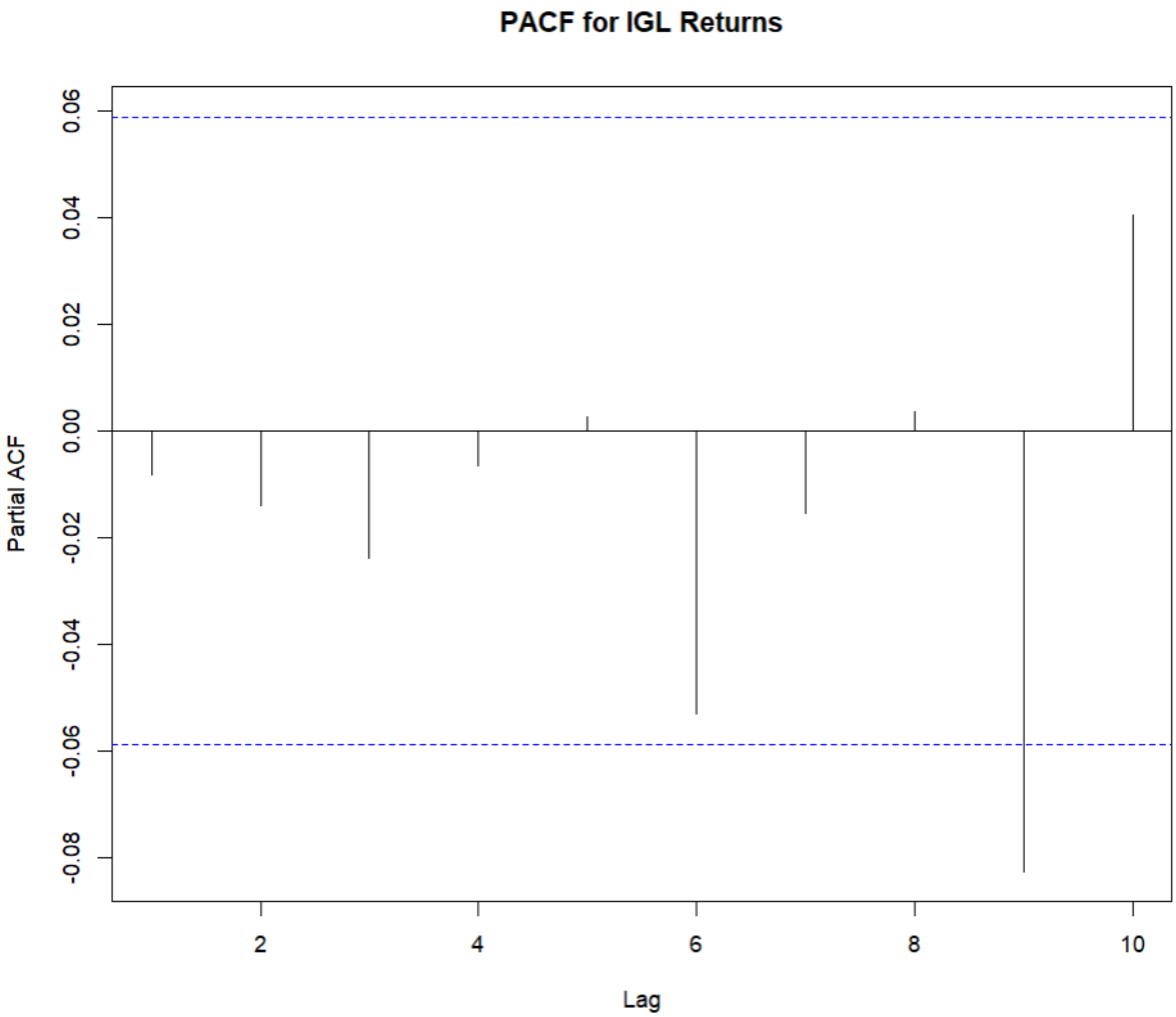
Fig. Augmented Dickey-Fuller Test for Daily Returns

ACF Plot:



The ACF plot shows a significant spike at lag 1, which indicates that the time series has a strong autocorrelation at this lag. This means that the current value is influenced by the immediate previous value. There is no clear pattern of decay, such as an exponential or sinusoidal decrease. A simple model, such as an AR(1) or MA(1) model, might be appropriate for this time series.

PACF Plot :



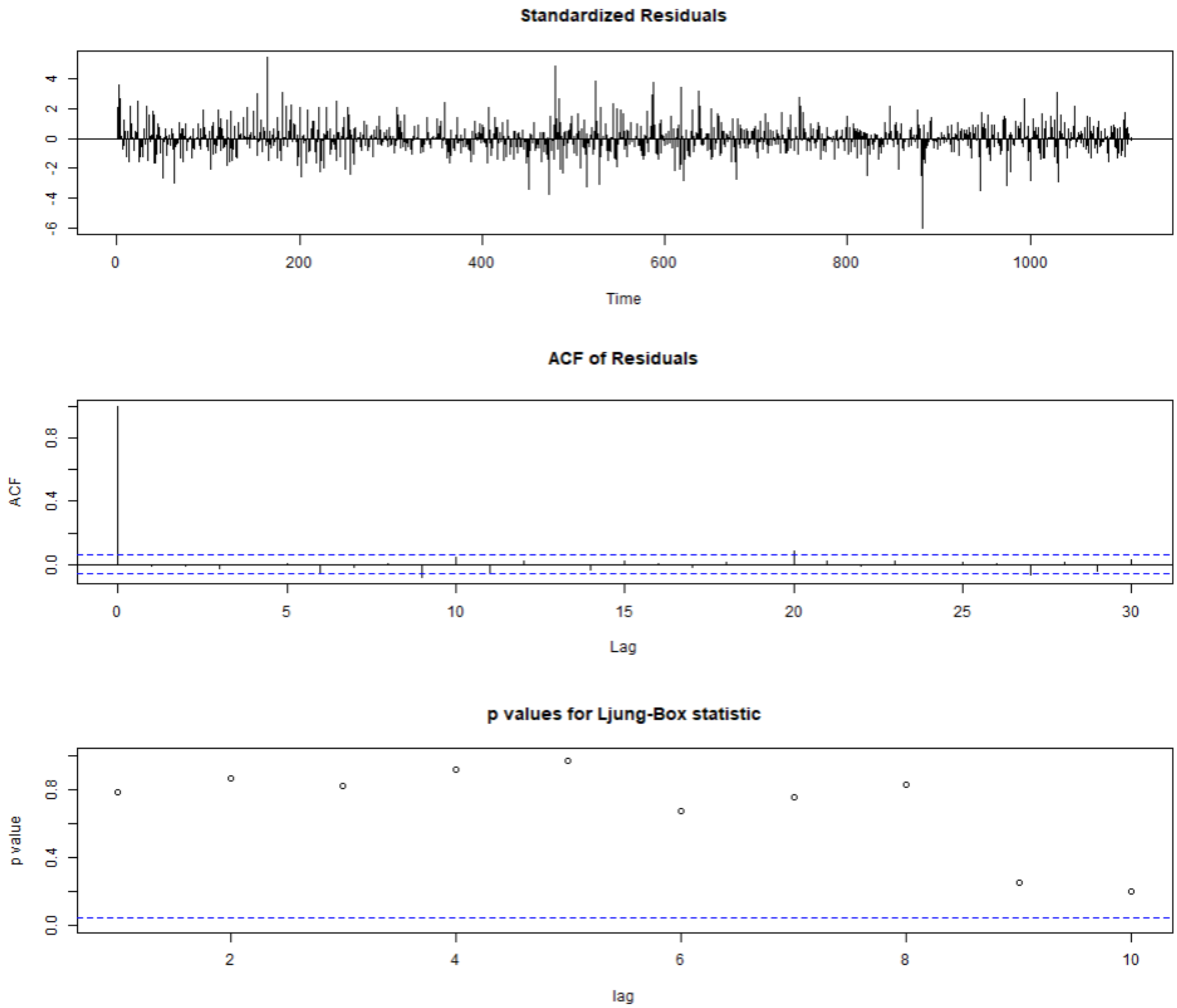
None of the lags in the observed PACF plot exceed the 95% confidence interval (the blue dashed lines) by a significantly large margin. This indicates that there are no statistically significant partial autocorrelations. This suggests weak dependence on past values. This PACF plot suggests that an AR model may not be necessary or useful for this series. Other approaches like moving average models (MA), combined models (ARMA) etc can be used.

Following this, the ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IGL)

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

Coefficients:
      intercept
          5e-04
s.e.      6e-04

sigma^2 estimated as 0.0003941:  log likelihood = 2778.02,  aic = -5552.04

Training set error measures:
                       ME       RMSE        MAE  MPE MAPE      MASE         ACF1
Training set 1.585491e-15 0.01985285 0.01433041 -Inf  Inf 0.6838094 -0.008262845
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test :



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IGL
     Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
1112   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1113   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1114   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1115   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1116   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1117   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1118   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1119   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1120   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1121   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
```

Forecasting Volatility using GARCH and EGARCH models:

```
*---------------------------------*
*       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
```

- We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.
- Now we can start by running the EGARCH model on the daily returns of the e-GARCH Model.

EGARCH

```
*---------------------------------*
*       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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

Estimating the model:

```
> ugfit_IGL

*---------------------------------*
*          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      0.000491    0.000561    0.87419  0.38202
ar1    -0.994349    0.003467 -286.77248  0.00000
ma1     0.985637    0.000206 4795.92071  0.00000
omega   0.000314    0.000046    6.80944  0.00000
alpha1  0.187049    0.028639    6.53127  0.00000
beta1   0.016266    0.120809    0.13464  0.89289

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.000491    0.000501    0.97881 0.327673
ar1    -0.994349    0.003049 -326.14286 0.000000
ma1     0.985637    0.000287 3428.43015 0.000000
omega   0.000314    0.000072    4.37387 0.000012
alpha1  0.187049    0.036477    5.12780 0.000000
beta1   0.016266    0.182458    0.08915 0.928963

LogLikelihood : 2804.432

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

Akaike       -5.0332
Bayes        -5.0061
Shibata      -5.0332
Hannan-Quinn -5.0229

Weighted Ljung-Box Test on Standardized Residuals
```

```
Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.01317  0.9086
Lag[2*(p+q)+(p+q)-1][5]   2.14272  0.5851
Lag[4*(p+q)+(p+q)-1][9]   5.12939  0.4106
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.02363 0.500 2.000  0.8778
ARCH Lag[5]   4.06035 1.440 1.667  0.1685
ARCH Lag[7]   6.35279 2.315 1.543  0.1192

Nyblom stability test
------------------------------------
Joint Statistic:  1.2368
Individual Statistics:
mu     0.12406
ar1    0.22996
ma1    0.19155
omega  0.56092
alpha1 0.07561
beta1  0.49756

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          0.08006 0.9362
Negative Sign Bias 0.03995 0.9681
Positive Sign Bias 0.33698 0.7362
Joint Effect       0.12477 0.9887


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     52.21    6.157e-05
2    30     63.07    2.524e-04
3    40     74.40    5.443e-04
4    50     93.31    1.397e-04


Elapsed time : 0.4325099
```

- The Log-likelihood of the model is 2804.432. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- For IGL Daily returns. Among the Optimal Parameters,only beta is significant as its p-value is lower than 0.05.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

GARCH Model Forecast:

```
> ugforecast_IGL

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

0-roll forecast [T0=2024-09-27]:
         Series   Sigma
T+1  -0.0005678 0.01787
T+2   0.0015433 0.01947
T+3  -0.0005559 0.01978
T+4   0.0015315 0.01984
T+5  -0.0005441 0.01985
T+6   0.0015197 0.01985
T+7  -0.0005324 0.01985
T+8   0.0015081 0.01985
T+9  -0.0005209 0.01985
T+10  0.0014967 0.01985
```

The above table shows the forecasted value using the GARCH model for the daily return.

ESTIMATING EGARCH FOR IGL

```
> egforecast_IGL

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

0-roll forecast [T0=2024-09-27]:
        Series   Sigma
T+1  0.0003249 0.01568
T+2  0.0003979 0.01708
T+3  0.0004520 0.01805
T+4  0.0004922 0.01871
T+5  0.0005220 0.01915
T+6  0.0005441 0.01944
T+7  0.0005605 0.01963
T+8  0.0005727 0.01976
T+9  0.0005817 0.01984
T+10 0.0005884 0.01989
```

The result of forecasting is shown in Figure . The results show that the returns will be positive on average for the next 10 days, with a mean value of 0.04% and a standard deviation of 3.5%.

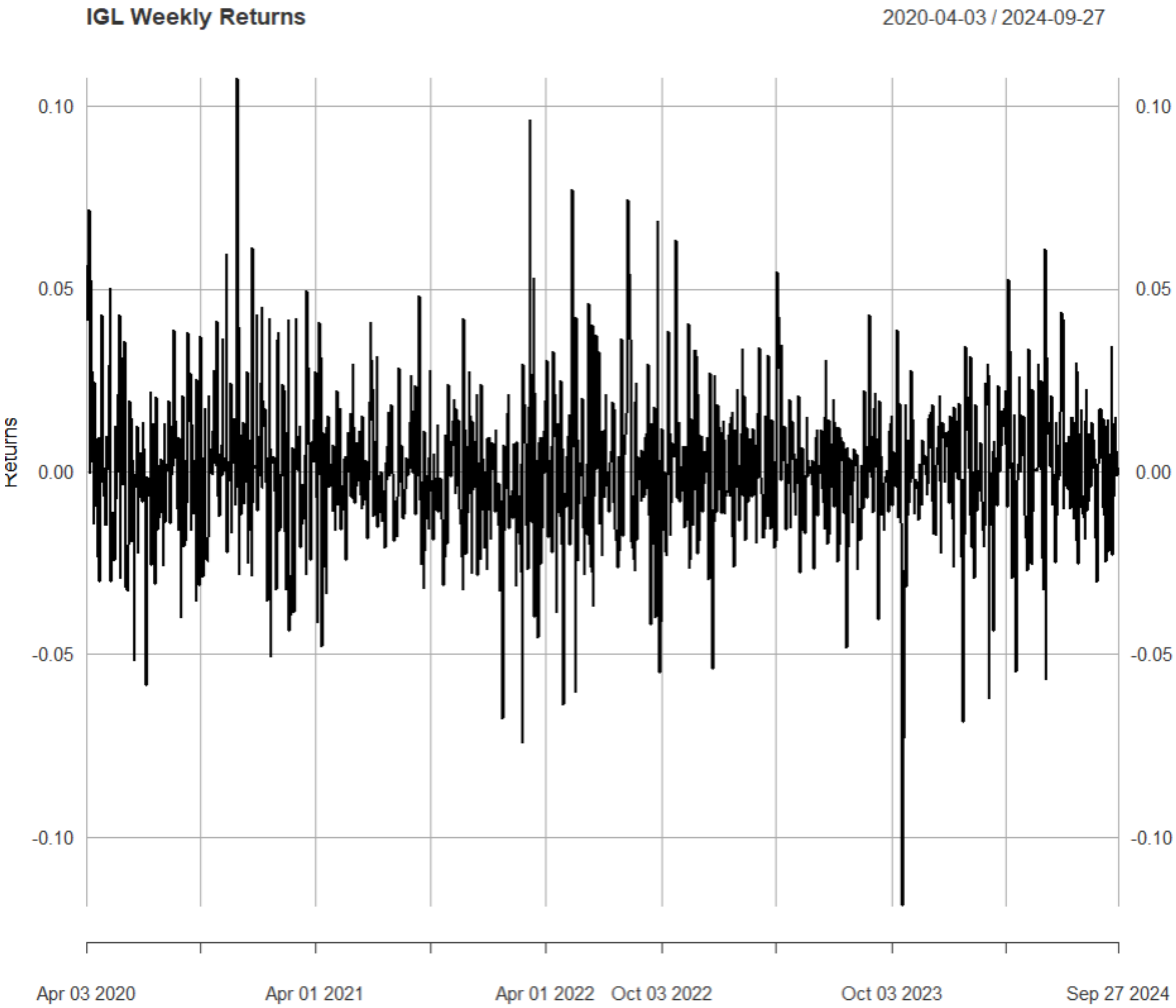
Weekly Returns

- **CAPM Analysis**

```
Call:
lm(formula = IGL.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
     Min       1Q   Median       3Q      Max
-0.13706 -0.02292 -0.00009  0.01756  0.20743

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -0.005610   0.002918  -1.923   0.0559 .
NSEI.ExcessReturns  0.759648   0.115148   6.597 3.47e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03981 on 206 degrees of freedom
Multiple R-squared:  0.1744,    Adjusted R-squared:  0.1704
F-statistic: 43.52 on 1 and 206 DF,  p-value: 3.47e-10
```

Weekly Returns (Beta = 0.759)

Interpretation:
The weekly beta of 0.759 further emphasizes IGL's stability. The stock remains less sensitive to market trends even over a weekly timeframe, making it an attractive choice for medium-term investors seeking low-risk exposure. This consistent defensiveness can be attributed to the predictable nature of its revenue streams and its position in the regulated utility sector. Investors can rely on IGL for steady growth, even in volatile market conditions.

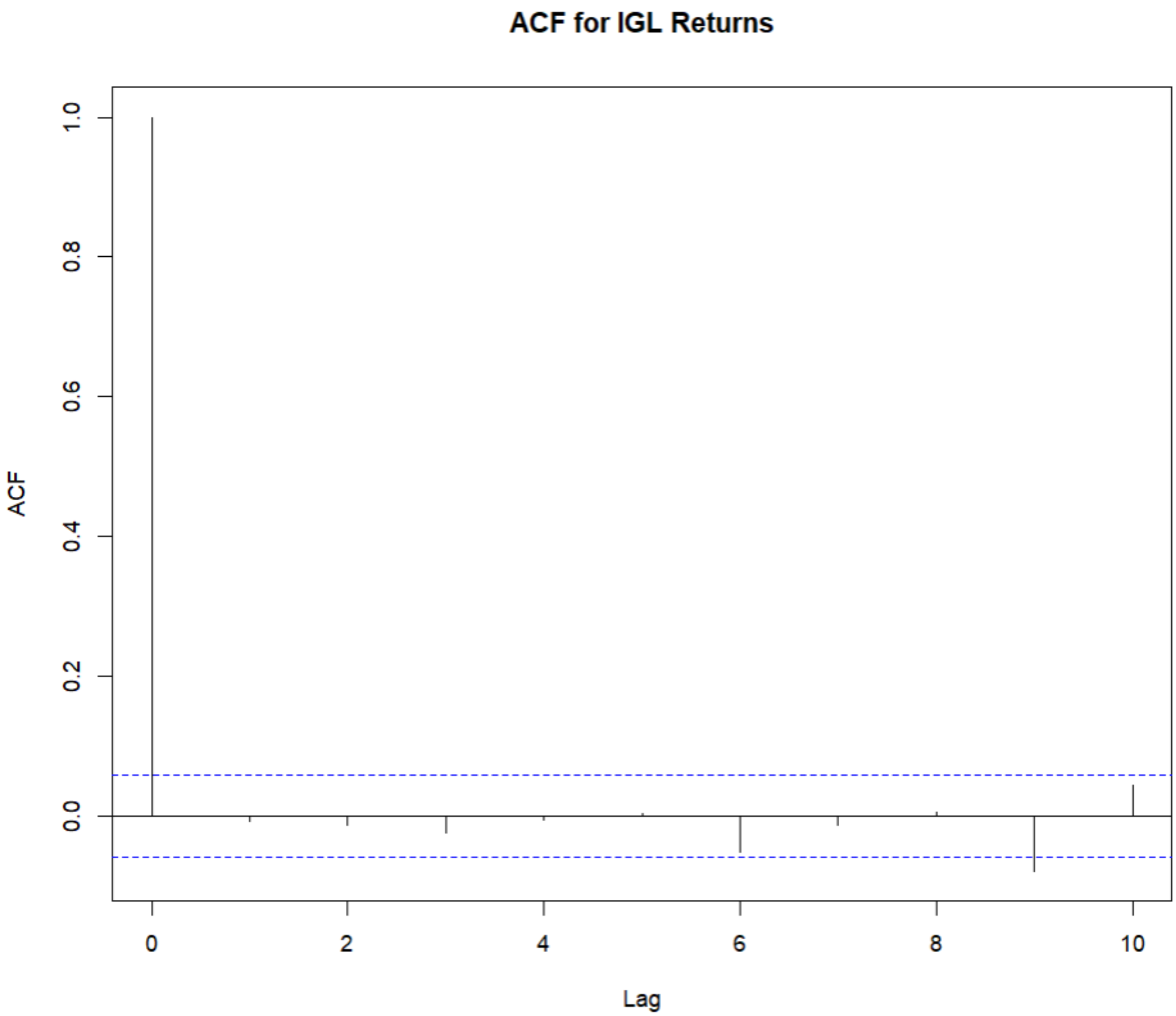


Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01 which is less than 0.05 or 5%. The experiments yielded the following results:

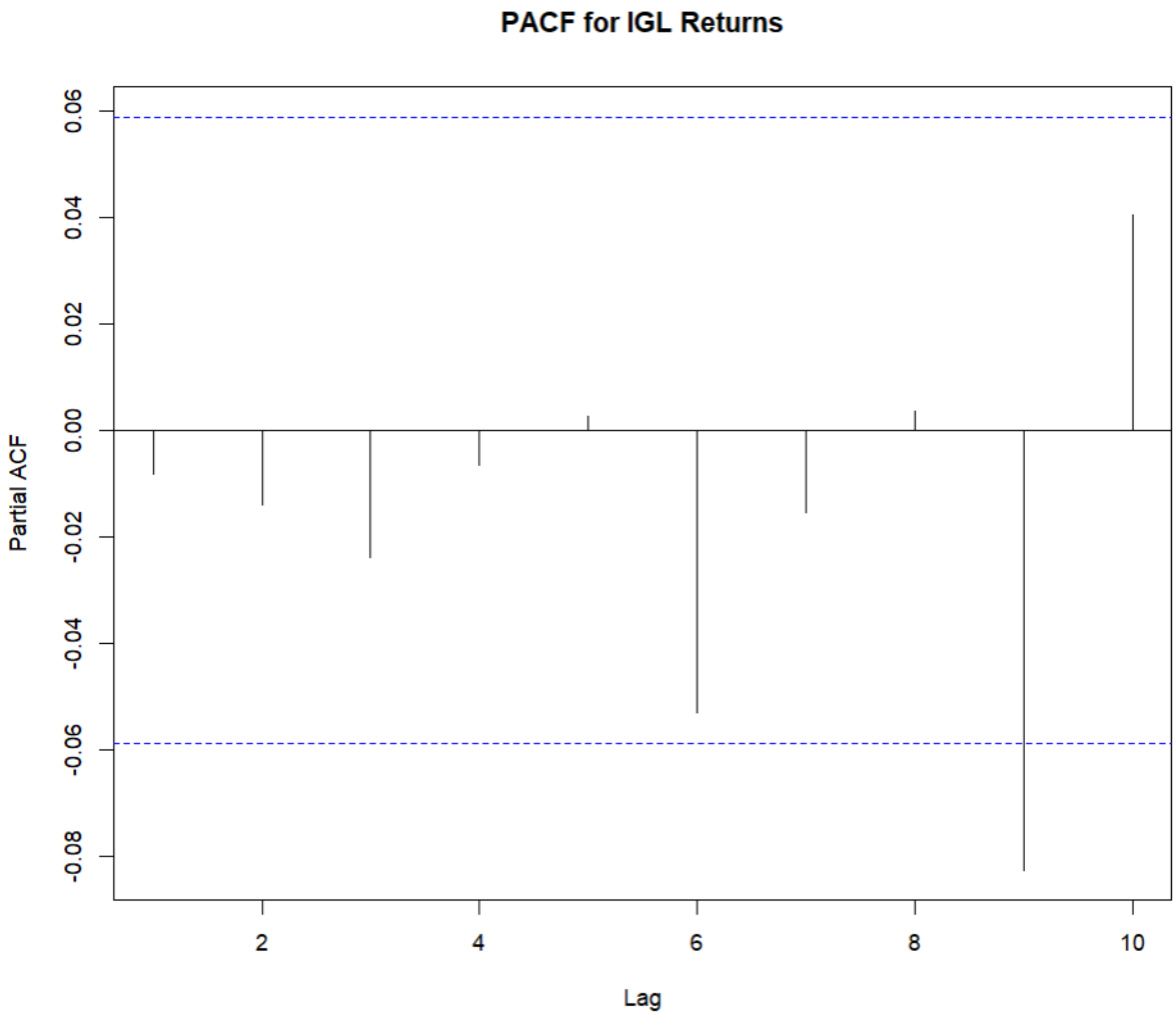
```
> adf.test(returns_IGL, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  returns_IGL
Dickey-Fuller = -11.329, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot:



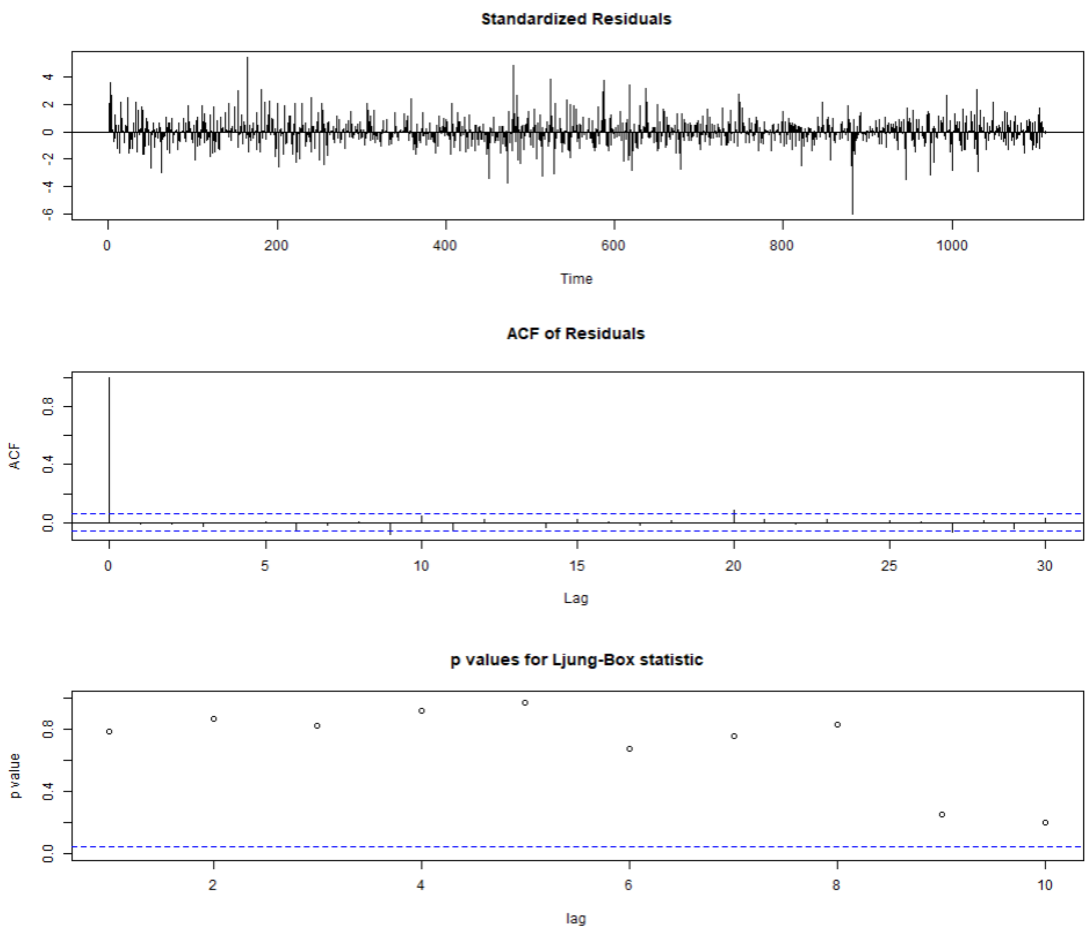
Most of the lags have values within the confidence interval, suggesting no significant partial correlation. Few lags have PACF values outside the confidence interval, indicating statistically significant partial correlations. Based on the analysis, AR(1) is a significant model that can be considered for this plot.

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IGL)

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

Coefficients:
      intercept
          5e-04
s.e.      6e-04

sigma^2 estimated as 0.0003941:  log likelihood = 2778.02,  aic = -5552.04
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IGL
     Point Forecast      Lo 80      Hi 80       Lo 95      Hi 95
1112   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1113   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1114   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1115   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1116   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1117   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1118   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1119   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1120   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
1121   0.0005041586 -0.0249383 0.02594661 -0.03840672 0.03941504
```

GARCH & EGARCH:

-Weekly Garch

```
> 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
```

- We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.
- Now we can start by running the EGARCH model on the daily returns of e-GARCH Model.

```
> 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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

-GARCH Model Fitting

```
> ugfit_IGL

*---------------------------------*
*          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      0.002278    0.002196    1.037388 0.299555
ar1     0.522176    0.334139    1.562748 0.118112
ma1    -0.618552    0.306746   -2.016497 0.043748
omega   0.000001    0.000003    0.276965 0.781807
alpha1  0.000000    0.000302    0.000002 0.999999
beta1   0.999000    0.000254 3932.950279 0.000000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.002278    0.002296    0.99232 0.321040
ar1     0.522176    0.226042    2.31009 0.020883
ma1    -0.618552    0.221666   -2.79047 0.005263
omega   0.000001    0.000008    0.10669 0.915032
alpha1  0.000000    0.001549    0.00000 1.000000
beta1   0.999000    0.000640 1561.27860 0.000000

LogLikelihood : 412.1461
```

```
LogLikelihood : 412.1461

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

Akaike       -3.4419
Bayes        -3.3539
Shibata      -3.4432
Hannan-Quinn -3.4064

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2018  0.6532
Lag[2*(p+q)+(p+q)-1][5]    3.3935  0.2525
Lag[4*(p+q)+(p+q)-1][9]    7.1534  0.1140
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1042  0.7468
Lag[2*(p+q)+(p+q)-1][5]    0.8482  0.8930
Lag[4*(p+q)+(p+q)-1][9]    2.1677  0.8841
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.3589 0.500 2.000  0.5491
```

```
ARCH Lag[5]    1.5048 1.440 1.667  0.5910
ARCH Lag[7]    2.4937 2.315 1.543  0.6137

Nyblom stability test
------------------------------------
Joint Statistic:  20.9583
Individual Statistics:
mu     0.09856
ar1    0.11640
ma1    0.11796
omega  0.24826
alpha1 0.06235
beta1  0.08940

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            1.775 0.07715   *
Negative Sign Bias   1.398 0.16332
Positive Sign Bias   1.440 0.15109
Joint Effect         4.235 0.23722


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     23.49       0.2164
2    30     29.93       0.4174
3    40     45.69       0.2139
4    50     60.61       0.1236


Elapsed time : 0.07172203
```

Observations from the Diagnostic test for the GARCH model for Weekly Returns

● The resulting log-likelihood of the model is 412.146.

● GARCH(1,1) and corresponding ARFIMA(1,0,1) are best for weekly returns.

● The ALPHA and Omega parameters are derived by a fitting process of the GARCHmodel. The model's minimal AIC and BIC values are used to describe best fit.

-EGARCHE MODEL FITTING

```
> egfit_IGL

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.001755    0.002006  8.7506e-01 0.381543
ar1     0.498443    0.260770  1.9114e+00 0.055950
ma1    -0.595645    0.239336 -2.4887e+00 0.012820
omega  -0.202460    0.005534 -3.6583e+01 0.000000
alpha1 -0.071182    0.021782 -3.2679e+00 0.001084
beta1   0.968879    0.000000  4.2769e+06 0.000000
gamma1 -0.013981    0.009596 -1.4570e+00 0.145109

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.001755    0.001909  9.1974e-01 0.357708
ar1     0.498443    0.139052  3.5846e+00 0.000338
ma1    -0.595645    0.120370 -4.9484e+00 0.000001
omega  -0.202460    0.005784 -3.5002e+01 0.000000
alpha1 -0.071182    0.029319 -2.4279e+00 0.015187
beta1   0.968879    0.000000  3.6139e+06 0.000000
gamma1 -0.013981    0.009233 -1.5142e+00 0.129972

LogLikelihood : 417.7393

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

Akaike       -3.4808
Bayes        -3.3781
Shibata      -3.4825
Hannan-Quinn -3.4394
```

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                            statistic p-value
Lag[1]                         0.1056 0.74516
Lag[2*(p+q)+(p+q)-1][5]        3.5366 0.19162
Lag[4*(p+q)+(p+q)-1][9]        7.4162 0.09292
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                            statistic p-value
Lag[1]                         0.3306  0.5653
Lag[2*(p+q)+(p+q)-1][5]        1.3398  0.7792
Lag[4*(p+q)+(p+q)-1][9]        2.8702  0.7802
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.1134 0.500 2.000  0.7363
ARCH Lag[5]    1.5589 1.440 1.667  0.5770
ARCH Lag[7]    2.6691 2.315 1.543  0.5781

Nyblom stability test
------------------------------------
Joint Statistic:  0.9622
Individual Statistics:
mu     0.09058
ar1    0.18210
ma1    0.19063
omega  0.11472
alpha1 0.18023
beta1  0.11613
gamma1 0.03176

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           1.6166 0.1073
Negative Sign Bias  0.9393 0.3485
Positive Sign Bias  1.3824 0.1682
Joint Effect        3.1690 0.3663


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     15.36       0.6997
2    30     27.14       0.5644
3    40     32.47       0.7605
4    50     44.51       0.6556


Elapsed time : 0.1430068
```

- The log-likelihood of the model stands at 417.7393. For IGL returns, the optimal models identified are eGARCH(1,1) coupled with ARFIMA(1,0,1).
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-GARCHE MODEL FORECASTING

```
> ugforecast_IGL

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

0-roll forecast [T0=2024-09-29]:
         Series   Sigma
T+1  -0.0004763 0.03976
T+2   0.0008398 0.03975
T+3   0.0015270 0.03974
T+4   0.0018858 0.03973
T+5   0.0020732 0.03972
T+6   0.0021710 0.03971
T+7   0.0022221 0.03970
T+8   0.0022488 0.03969
T+9   0.0022627 0.03968
T+10  0.0022700 0.03967
```

The above table shows the forecasted value using the GARCH model for the daily return.

-EGARCHE MODEL FORECASTING

```
> egforecast_IGL

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

0-roll forecast [T0=2024-09-29]:
         Series   Sigma
T+1  -0.0011127 0.03389
T+2   0.0003259 0.03403
T+3   0.0010429 0.03416
T+4   0.0014003 0.03430
T+5   0.0015784 0.03442
T+6   0.0016672 0.03455
T+7   0.0017115 0.03467
T+8   0.0017336 0.03479
T+9   0.0017446 0.03490
T+10  0.0017500 0.03501
```

The result of forecasting is shown in Figure. The results show that the returns will mostly be positive on average for the next 10 days, with a mean value of 0.11% and a standard deviation of 3.5%.

Monthly Returns

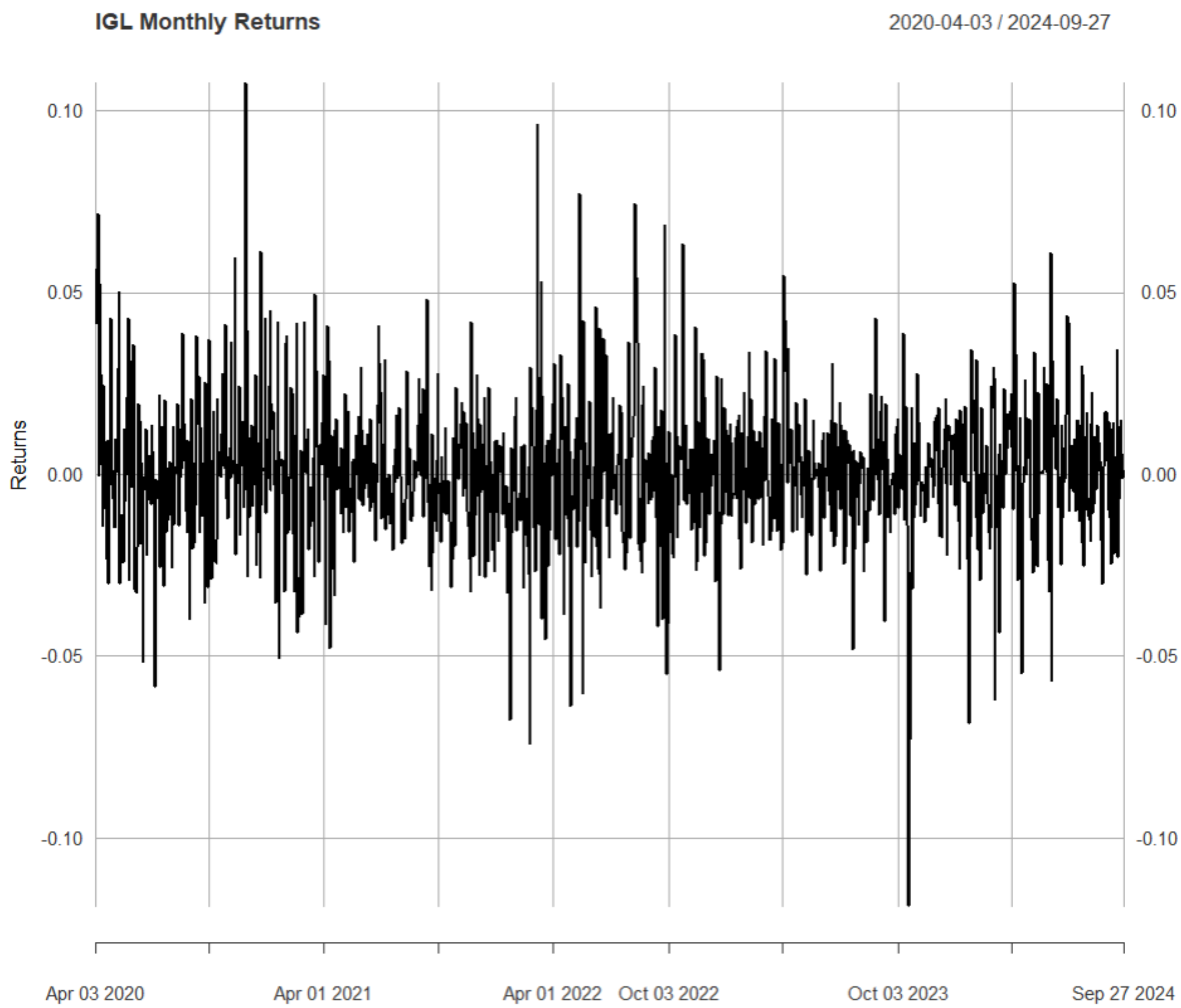
- **CAPM Analysis**

```
CAPM Regression Results for IGL.NS

Call:
lm(formula = exStock ~ exNSE, data = data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.186987 -0.044903 -0.000228  0.053386  0.188242

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.05080    0.03024   -1.68   0.0989 .
exNSE        0.91295    0.06953   13.13   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07484 on 53 degrees of freedom
Multiple R-squared:  0.7649,    Adjusted R-squared:  0.7604
F-statistic: 172.4 on 1 and 53 DF,  p-value: < 2.2e-16
```

Monthly Returns (Beta = 0.912)

Interpretation:

Over the long run, its beta goes up slightly to 0.912, which indicates a moderate level of co-movement with market trends. This means that even though the stock is stable and not so volatile in any two-period interval, in the long run, it shows a better response to broader economic and industry factors. Thus, for the investor, IGL presents a combination of stability and growth, making it ideal for portfolios seeking low-risk steady returns.



B. Estimating AR and MA coefficient using ARIMA model

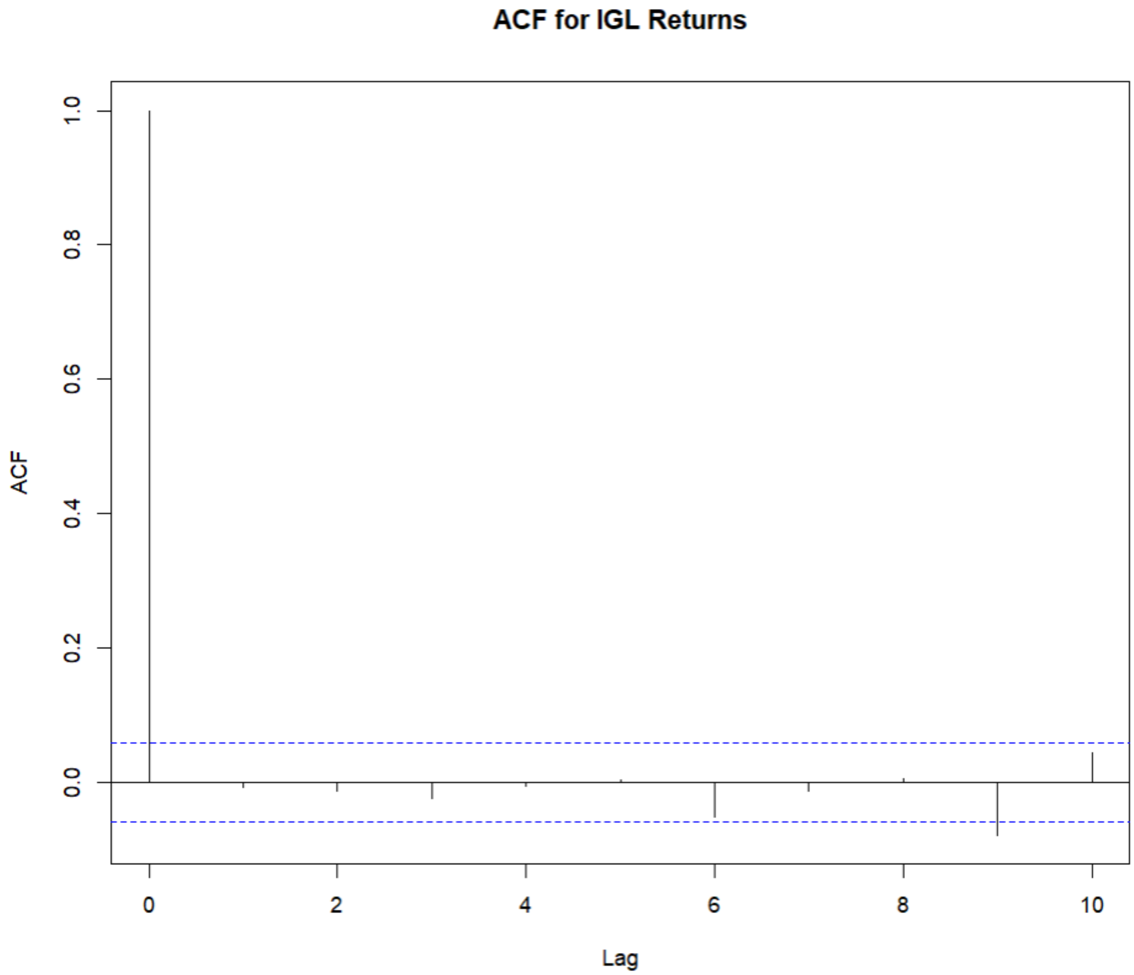
The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary.The p – value from the Augmented Dickey-Fuller Test is less than 0.05 which shows that the series is stationary.

The experiments yielded the following results:

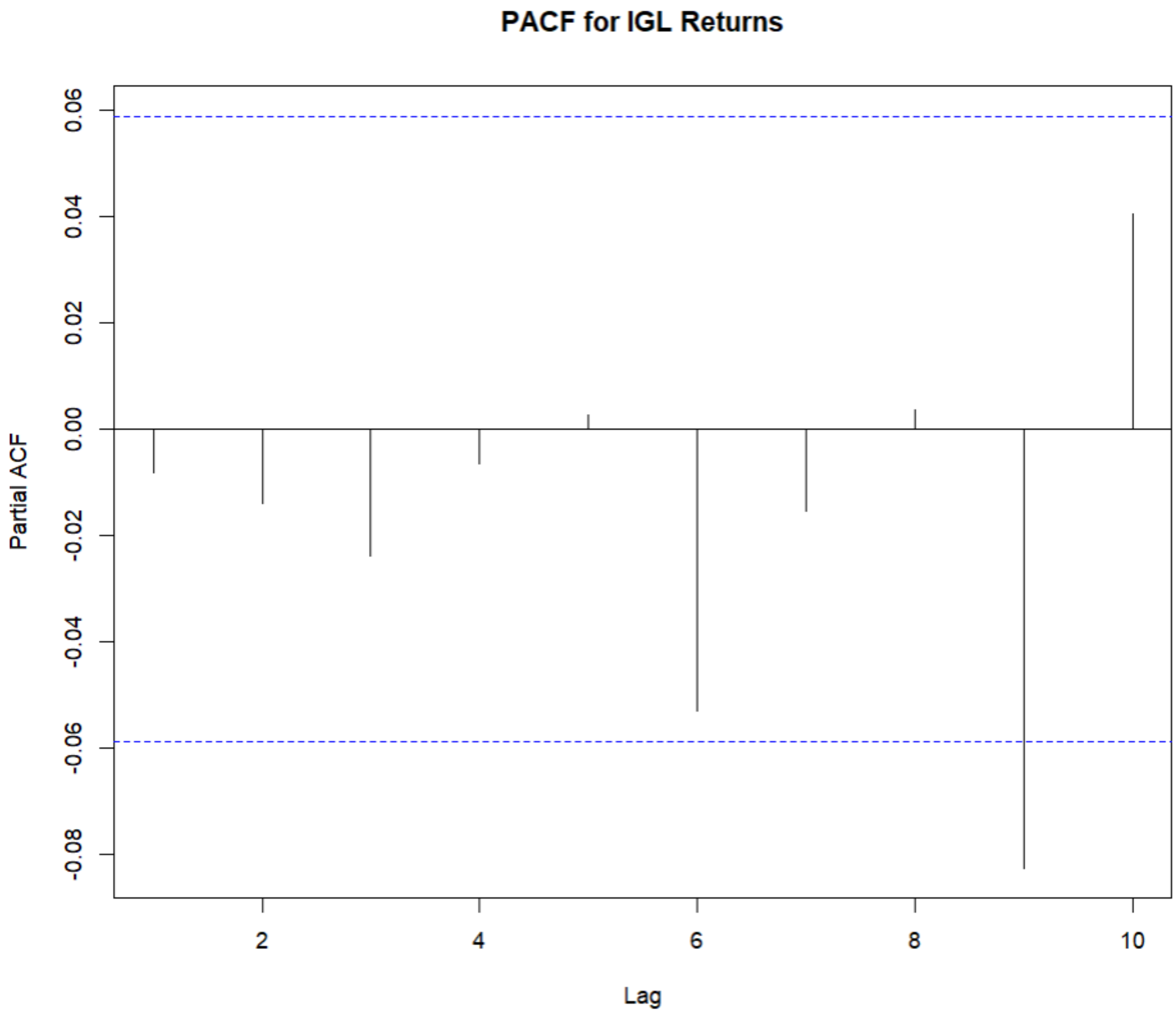
```
> adf.test(returns_IGL, alternative = "stationary")

	Augmented Dickey-Fuller Test

data:  returns_IGL
Dickey-Fuller = -11.329, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot :



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of ϕ1. ACF decays exponentially to 0 as the latency increases for negative ϕ1, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot :



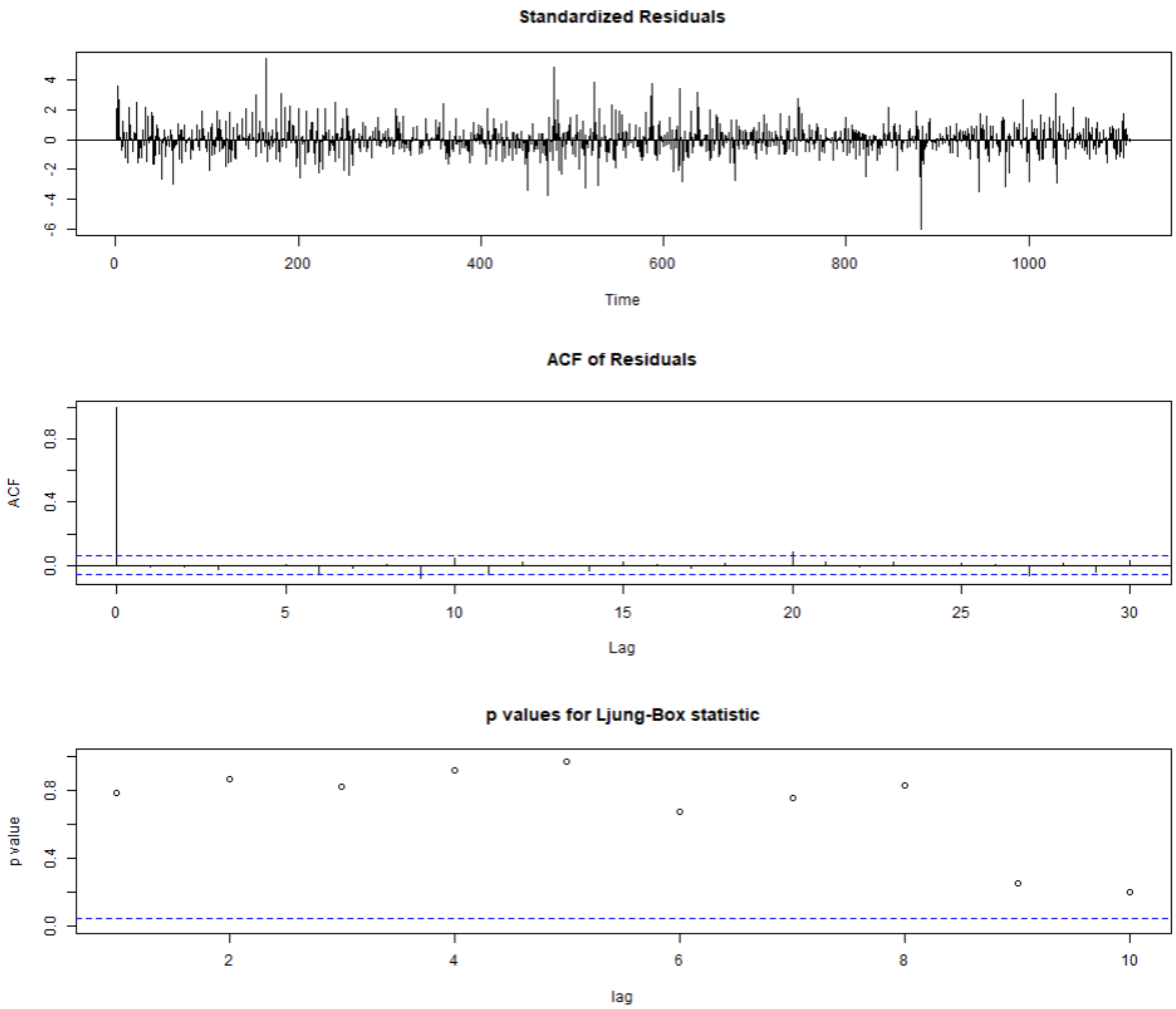
Based on the PACF plot, all lags appear to have autocorrelation values within the confidence intervals, indicating that they are statistically insignificant. The order of the autoregressive model can be taken as AR(0) since the time series data does not depend on past data.

```
> summary(arima_final_IGL)

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

Coefficients:
      intercept
          5e-04
s.e.      6e-04

sigma^2 estimated as 0.0003941:  log likelihood = 2778.02,  aic = -5552.04

Training set error measures:
                       ME       RMSE        MAE  MPE MAPE      MASE         ACF1
Training set 1.585491e-15 0.01985285 0.01433041 -Inf  Inf 0.6838094 -0.008262845
```

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test :



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Monthly Garche

```
> 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
```

- We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.
- Now we can start by running the EGARCH model on the daily returns of the e-GARCH Model.

-Monthly EGarche

```
> 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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

MODELLING GARCHE

```
> ugfit_IGL

*---------------------------------*
*          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      0.007656    0.001531   5.002014 0.000001
ar1     0.857015    0.069575  12.317928 0.000000
ma1    -1.000000    0.076011 -13.156041 0.000000
omega   0.000000    0.000070   0.000000 1.000000
alpha1  0.000000    0.018926   0.000012 0.999990
beta1   0.995015    0.018614  53.455413 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.007656    0.005227  1.464722  0.14300
ar1     0.857015    0.089040  9.625106  0.00000
ma1    -1.000000    0.127936 -7.816402  0.00000
omega   0.000000    0.000026  0.000001  1.00000
alpha1  0.000000    0.018254  0.000013  0.99999
beta1   0.995015    0.016627 59.843546  0.00000

LogLikelihood : 61.7002

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

Akaike       -2.0630
Bayes        -1.8420
Shibata      -2.0845
Hannan-Quinn -1.9777

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

```
------------------------------------
                        statistic p-value
Lag[1]                     0.1049  0.7460
Lag[2*(p+q)+(p+q)-1][5]    0.8174  1.0000
Lag[4*(p+q)+(p+q)-1][9]    1.4304  0.9978
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.3085  0.5786
Lag[2*(p+q)+(p+q)-1][5]    2.2870  0.5523
Lag[4*(p+q)+(p+q)-1][9]    5.6047  0.3462
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.109 0.500 2.000  0.2924
ARCH Lag[5]     2.205 1.440 1.667  0.4278
ARCH Lag[7]     4.701 2.315 1.543  0.2565

Nyblom stability test
------------------------------------
Joint Statistic:  8.1988
Individual Statistics:
mu     0.09944
ar1    0.11789
ma1    0.42430
omega  0.03485
alpha1 0.02769
beta1  0.04207

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           0.6343 0.5289
Negative Sign Bias  0.1320 0.8955
Positive Sign Bias  0.4890 0.6270
Joint Effect        1.6426 0.6498
```

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     28.22      0.07924
2    30     31.56      0.33972
3    40     45.26      0.22704
4    50     55.26      0.25018


Elapsed time : 0.09478807
```

- The Log-likelihood of the model is 61.7002. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

MODELLING EGARCHE

```
> egfit_IGL

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.009444    0.000011  -890.37        0
ar1    -0.146654    0.000112 -1306.78        0
ma1     0.193783    0.000107  1810.25        0
omega  -0.877390    0.000180 -4863.15        0
alpha1 -0.344330    0.000051 -6714.01        0
beta1   0.824470    0.000165  4986.54        0
gamma1 -0.827197    0.000155 -5349.63        0

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.009444    0.000019 -502.823        0
ar1    -0.146654    0.012023  -12.198        0
ma1     0.193783    0.013211   14.668        0
omega  -0.877390    0.028300  -31.003        0
alpha1 -0.344330    0.018347  -18.767        0
beta1   0.824470    0.031668   26.035        0
gamma1 -0.827197    0.031190  -26.522        0

LogLikelihood : 72.78352
```

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

Akaike       -2.4364
Bayes        -2.1786
Shibata      -2.4652
Hannan-Quinn -2.3370

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.2479  0.6186
Lag[2*(p+q)+(p+q)-1][5]    1.2528  0.9998
Lag[4*(p+q)+(p+q)-1][9]    2.3490  0.9643
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1961  0.6579
Lag[2*(p+q)+(p+q)-1][5]    1.5381  0.7305
Lag[4*(p+q)+(p+q)-1][9]    3.2743  0.7129
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.2007 0.500 2.000  0.6542
ARCH Lag[5]    0.6483 1.440 1.667  0.8391
ARCH Lag[7]    2.0089 2.315 1.543  0.7154
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  0.988
Individual Statistics:
mu     0.02913
ar1    0.02801
ma1    0.02776
omega  0.04223
alpha1 0.02880
beta1  0.07015
gamma1 0.02880

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           1.0634 0.2928
Negative Sign Bias  0.9759 0.3339
Positive Sign Bias  0.2637 0.7931
Joint Effect        1.4517 0.6935


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     23.04       0.2357
2    30     30.44       0.3921
3    40     43.78       0.2759
4    50     46.00       0.5955


Elapsed time : 0.2512181
```

- The Log-likelihood of the model is 61.7002. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be

rejected and hence the observed values and expected values do not differ by a lot.

FORECASTING GARCHE

```
> ugforecast_IGL

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

0-roll forecast [T0=2024-08-31]:
         Series   Sigma
T+1  -0.0070576 0.06780
T+2  -0.0049538 0.06763
T+3  -0.0031508 0.06747
T+4  -0.0016057 0.06730
T+5  -0.0002814 0.06713
T+6   0.0008535 0.06696
T+7   0.0018261 0.06679
T+8   0.0026597 0.06663
T+9   0.0033740 0.06646
T+10  0.0039862 0.06630
```

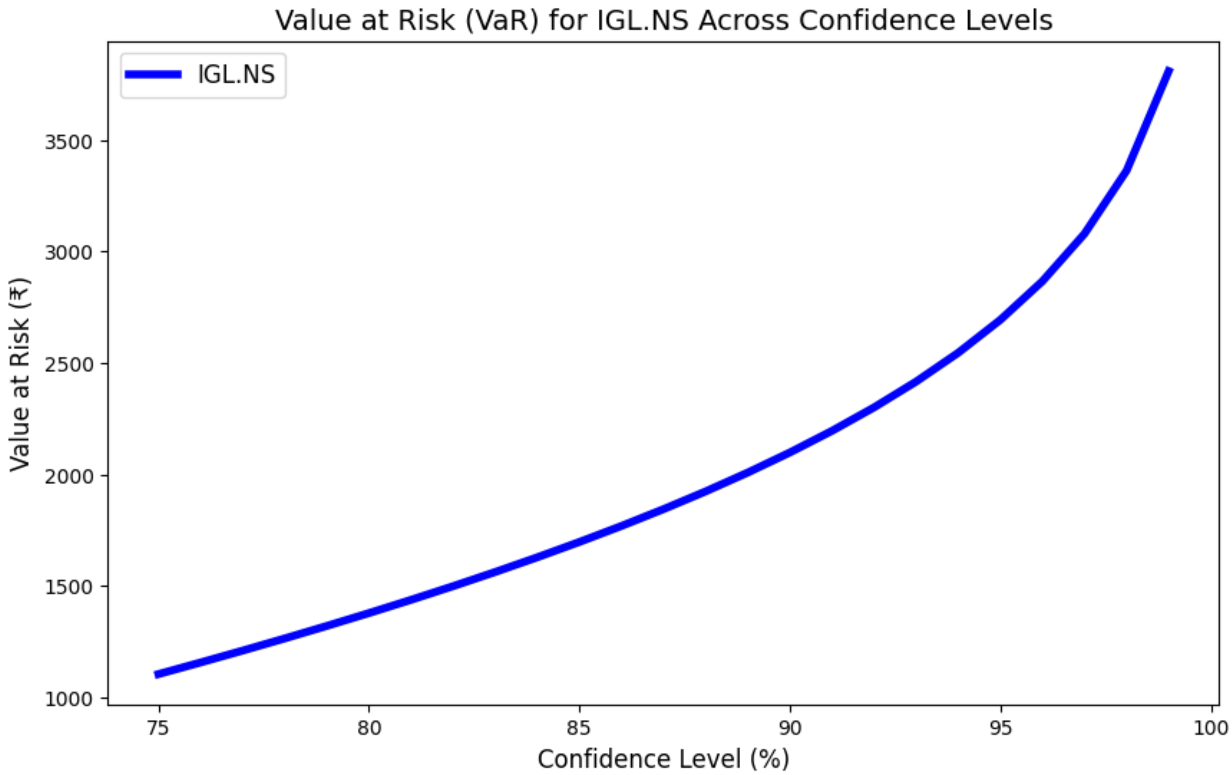
The above table shows the forecasted value using the GARCH model for the daily return.

FORECASTING EGARCHE

```
> ugforecast_IGL

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

0-roll forecast [T0=2024-08-31]:
         Series   Sigma
T+1  -0.0070576 0.06780
T+2  -0.0049538 0.06763
T+3  -0.0031508 0.06747
T+4  -0.0016057 0.06730
T+5  -0.0002814 0.06713
T+6   0.0008535 0.06696
T+7   0.0018261 0.06679
T+8   0.0026597 0.06663
T+9   0.0033740 0.06646
T+10  0.0039862 0.06630
```

The result of forecasting is shown in Figure . The results show that the returns fluctuate for the next 10 days, with a mean value of 0.04% and a standard deviation of 6.1%.

Calculating Value at Risk For IGL:-



Value at Risk (VaR) calculates the possible decline in the value of an investment or portfolio over a given period of time, assuming a particular degree of confidence (e.g., 95% or 99%).It helps investors and institutions comprehend the worst-case scenario under typical market conditions by giving them a measurable indicator of downside risk.

Above is the graph for IGL, showing the value at risk at different confidence intervals from 75% to 100%. At 75% confidence level, VaR is 1,000, which means that there is only a 25% chance that the stock price will fall by 1,000 rupees in a day. Similarly, VaR at 95% confidence level is 2,500, which means that there is only a 5% chance that the stock price will fall by 2,500 rupees in a day. At 100% confidence level, there is no chance that the stock price will fall by more than 3,500 rupees.

IDFC (Infrastructure Development Finance Company.)

-The company allotted to our group was IDFC:NS. However, the stock was merged with the larger IDFC FIRST Group stock as part of a merger (under which every IDFC shareholders received 155 fully paid up equity shares of IDFC First for every 100 shares). Due to this, all the historical data required for analysis for IDFC:NS could not be retrieved on R using Yahoo Finance library because the stock didn't existed anymore due to which the latter merged stock IDFCFIRSTB:NS has been included in the analysis instead.

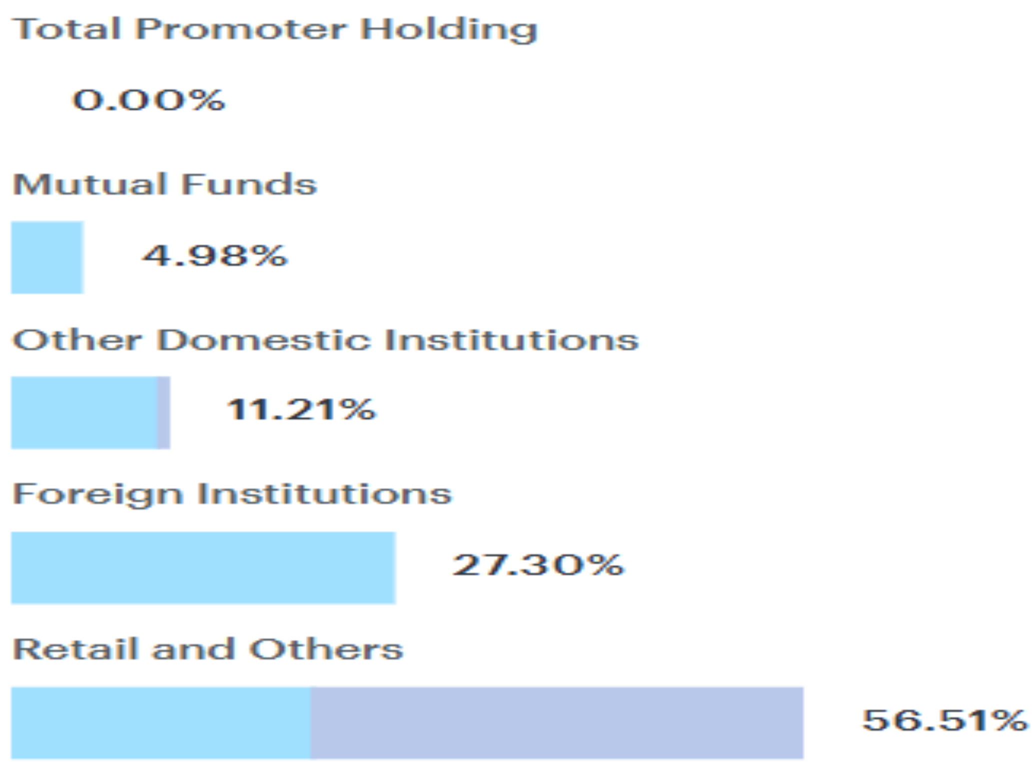
2. About the company

1.1.1 Nature of the business

IDFC FIRST Bank Limited is an Indian private sector bank resulting from the merger of IDFC Bank and Capital First, market effective date 2018. This bank offers the full gamut of banking activities like retail banking, wholesale banking, and wealth management services to its individual as well as corporate clients with special emphasis on loans, personal finance, and customized solutions. Its head office is based in Mumbai, Maharashtra, India, and it is distributed across various branches all over the country.

1.1.2 Ownership category

IDFC FIRST Bank is listed on the BSE and NSE of India. It was originally promoted by IDFC Ltd., a financial conglomerate partly owned by the Government of India. Now, following the capital First merger, it is structured as an institutionally invested full-service bank with retail shareholders holding significant stakes. Thus, it is an independent, private sector financial institution.



IDFCFIRST Shareholding Pattern

1.1.3 When did it start?

IDFC Bank was established in 2015 by IDFC Limited, following the latter's acquisition of a banking license from the RBI. In December 2018, the company merged with Capital First to create IDFC FIRST Bank. From its establishment, the infrastructure of IDFC Bank would now meet the acumen expertise with which the retail and SME lending business of Capital First would thus be giving birth to a stronger entity with enhanced retail banking capabilities.

1.1.4. Significance in the industry

IDFC FIRST Bank has become a significant player in Indian banking based on its retail-centric approach and very strong focus on digital transformation. Its customer-friendly initiatives such as zero-fee banking for various services, competitive loan rates, and innovative digital banking solutions make it stand out. It has been very active in supporting financial inclusion and scaling presence in under-served markets, aligning with the growth story of India.

1.1.5. Overall greatness of the company

IDFC FIRST Bank holds brilliant innovative ideas in offering customer-first banking solutions. So far, it has been a trusted financial partner building on technology-driven services, comprehensive risk management practices, and good customer satisfaction. IDFC FIRST Bank is aptly positioned for long-term growth and will significantly contribute to India's financial landscape with its commitment to retail finance, competitive product offerings, and responsible lending.

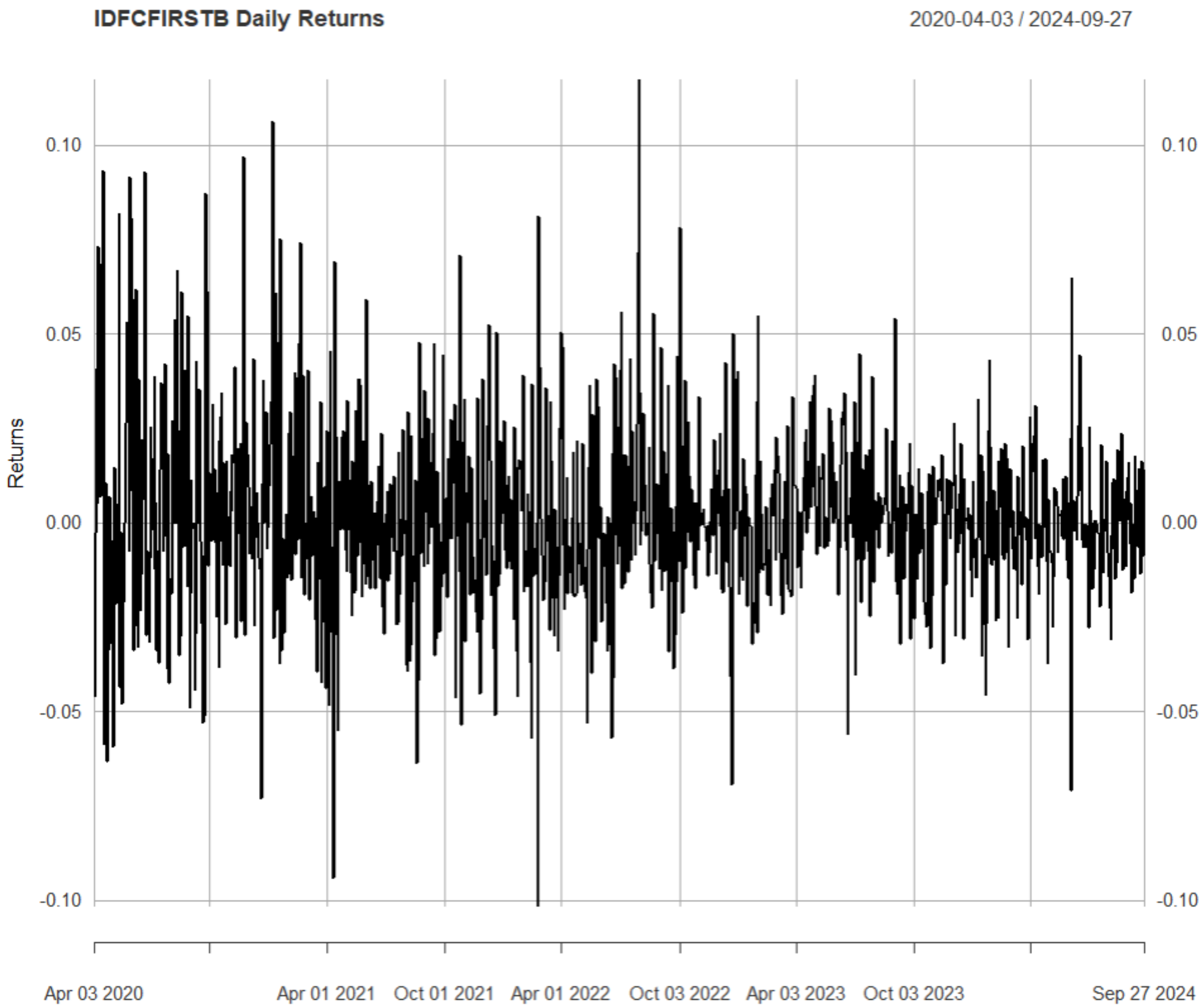
A. CAPM Analysis

```
Call:
lm(formula = IDFCFIRSTB.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.072831 -0.011758 -0.001694  0.009571  0.105689 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        0.0034038  0.0009528   3.573 0.000371 ***
NSEI.ExcessReturns 1.2429582  0.0569842  21.812  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02012 on 967 degrees of freedom
Multiple R-squared:  0.3298,	Adjusted R-squared:  0.3291 
F-statistic: 475.8 on 1 and 967 DF,  p-value: < 2.2e-16
```

Returns on Daily-Basis (Beta = 1.243)

Interpretation:

IDFC FIRST Bank daily beta is at 1.243, meaning that on a daily basis, it is much more volatile than the market, with its return changing by 1.243% in the same direction for every 1% change in the market. Higher sensitivity means that this is a riskier investment for short-term traders because while this definitely positions it as a riskier investment for short-term traders, it also maybe one that can deliver higher returns in a bullish market.



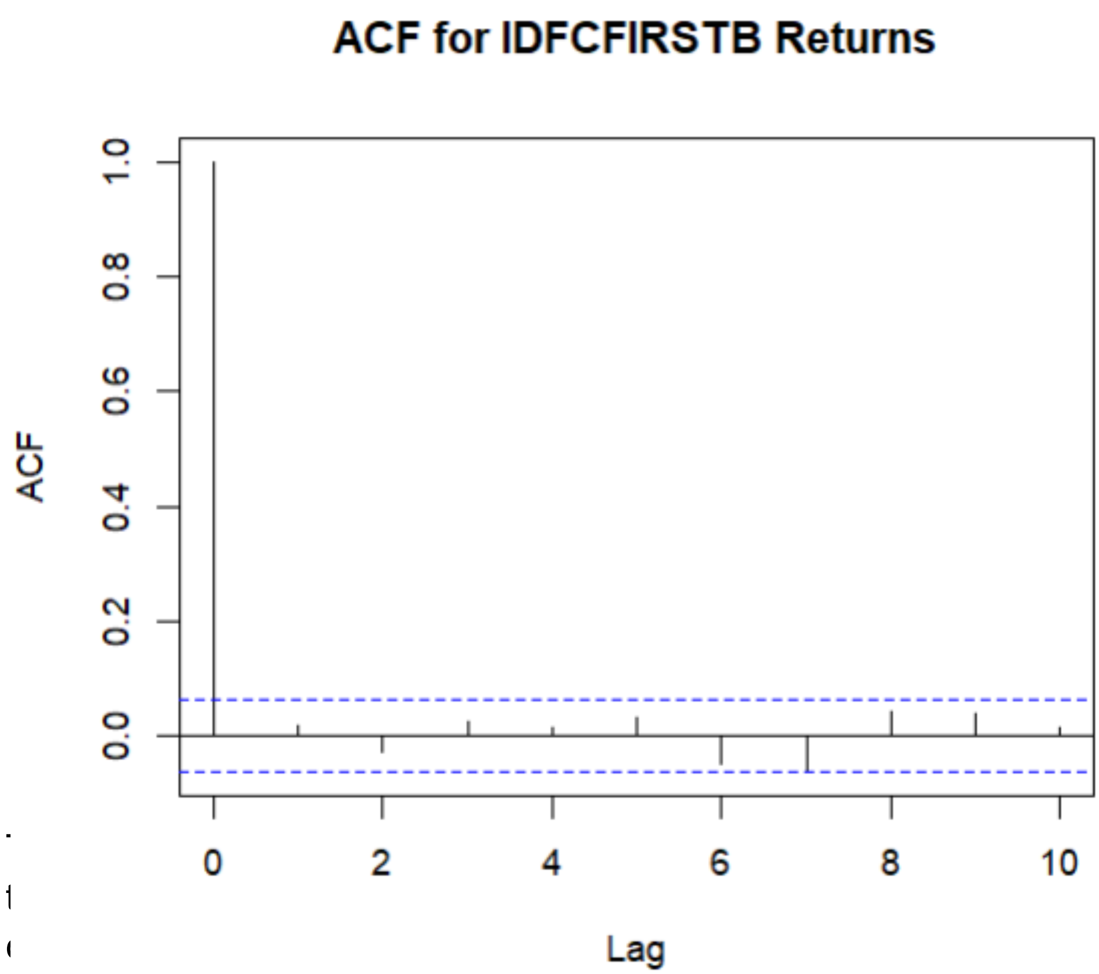
Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots. An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01, which is less than 0.05 or 5%. Hence, the series is stationary and rejects the null hypothesis. The experiments yielded the following results:

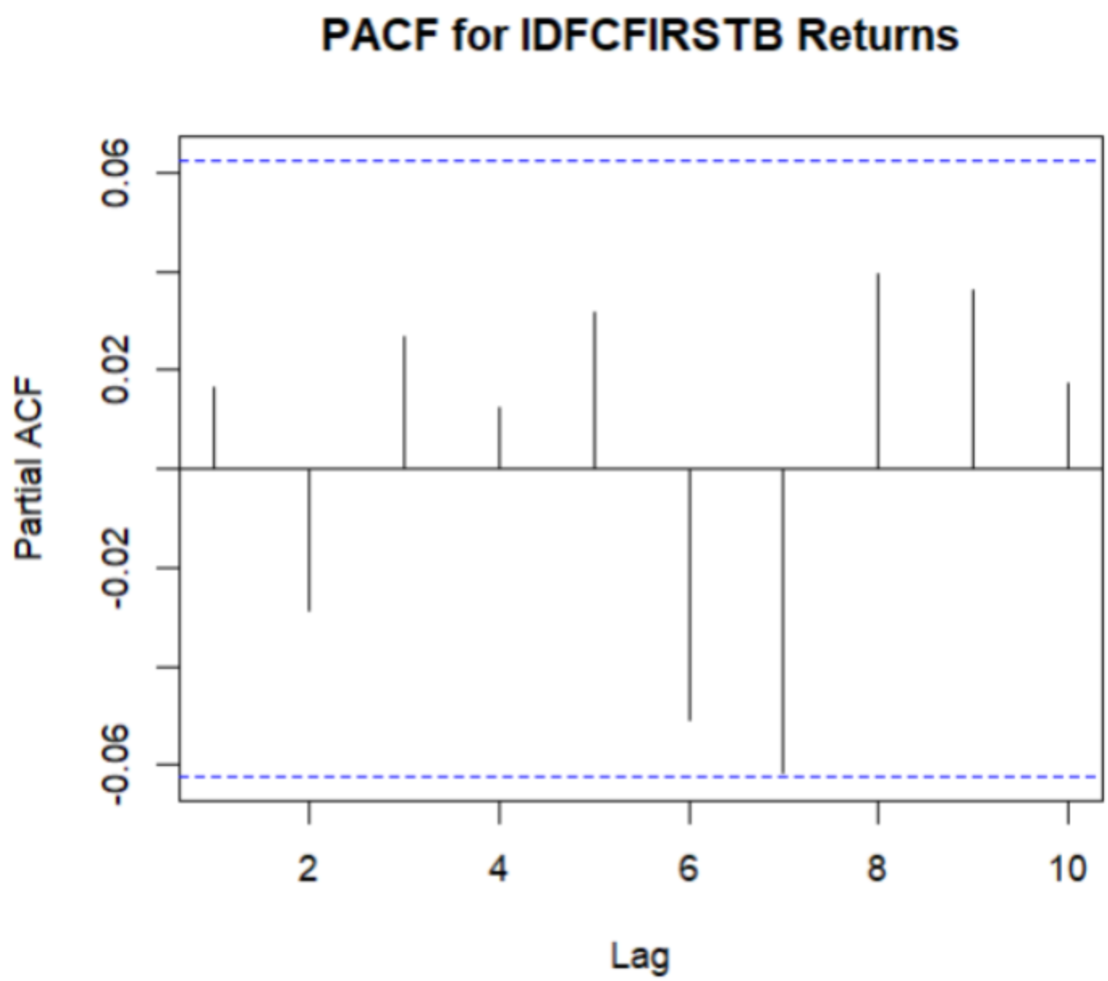
```
        Augmented Dickey-Fuller Test

data:  returns_IGL
Dickey-Fuller = -11.329, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



the
he
no
clear pattern of decay, such as an exponential or sinusoidal decrease. A simple model, such as an AR(1) or MA(1) model, might be appropriate for this time series.

PACF Plot :



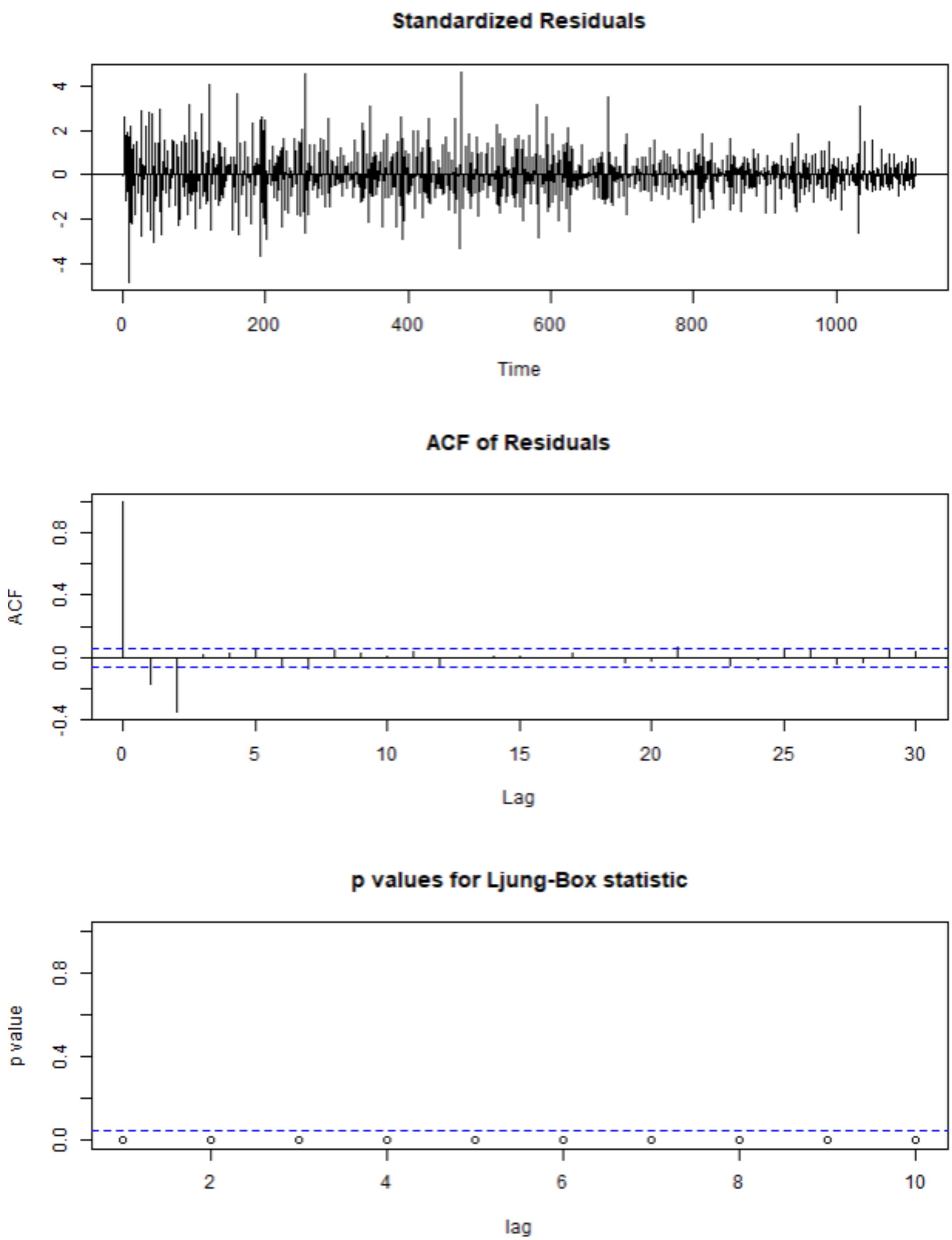
None of the lags in the observed PACF plot exceed the 95% confidence interval (the blue dashed lines) by a significant large margin. This indicates that there are no statistically significant partial autocorrelations. This suggests weak dependence on past values. This PACF plot suggests that an AR model may not be necessary or useful for this series. Other approaches like moving average models (MA), combined models (ARMA) etc can be used.

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> arima_final_IDFCFIRSTB <- arima(returns_IDFCFIRSTB, order = c(0,0,0))
> summary(arima_final_IDFCFIRSTB)

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

Coefficients:
      intercept
         0.0016
s.e.     0.0008

sigma^2 estimated as 0.0005899:  log likelihood = 2271.27,  aic = -4538.53

Training set error measures:
                        ME       RMSE        MAE  MPE MAPE      MASE       ACF1
Training set -3.433796e-15 0.02428756 0.01760677 -Inf  Inf 0.7046671 0.01637272
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test :



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are

often less than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IDFCFIRSTB <- forecast(arima_final_IDFCFIRSTB, h = 10)
> predicted_IDFCFIRSTB
    Point Forecast       Lo 80      Hi 80      Lo 95      Hi 95
989    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
990    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
991    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
992    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
993    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
994    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
995    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
996    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
997    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
998    0.001606635 -0.02951912 0.03273239 -0.0459961 0.04920937
```

Forecasting Volatility using GARCH and EGARCH models:

```
*---------------------------------*
*       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
```

- We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.
- Now we can start by running the EGARCH model on the daily returns of e-GARCH Model.

EGARCH

```
*---------------------------------*
*       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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

Estimating the model:

- -Estimating Garch model for IDFCFIRSTB

```
> ugfit_IDFCFIRSTB

*---------------------------------*
*          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      0.001015    0.000632   1.606590  0.10814
ar1     0.313060    3.149574   0.099397  0.92082
ma1    -0.315259    3.122533  -0.100963  0.91958
omega   0.000000    0.000001   0.251030  0.80179
alpha1  0.012100    0.001174  10.306437  0.00000
beta1   0.986501    0.001018 968.736047  0.00000
```

```
Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.001015    0.000648   1.566843  0.11715
ar1     0.313060    3.415296   0.091664  0.92697
ma1    -0.315259    3.418454  -0.092223  0.92652
omega   0.000000    0.000004   0.045540  0.96368
alpha1  0.012100    0.001498   8.079967  0.00000
beta1   0.986501    0.001214 812.769502  0.00000

LogLikelihood : 2648.301

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

Akaike       -4.7523
Bayes        -4.7253
Shibata      -4.7524
Hannan-Quinn -4.7421

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.002663  0.9588
Lag[2*(p+q)+(p+q)-1][5]  0.198737  1.0000
Lag[4*(p+q)+(p+q)-1][9]  2.277849  0.9694
d.o.f=2
H0 : No serial correlation
```

```
------------------------------------
                        statistic   p-value
Lag[1]                      28.22 1.086e-07
Lag[2*(p+q)+(p+q)-1][5]     28.47 8.543e-08
Lag[4*(p+q)+(p+q)-1][9]     29.24 7.024e-07
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.01806 0.500 2.000  0.8931
ARCH Lag[5]   0.32290 1.440 1.667  0.9341
ARCH Lag[7]   0.42842 2.315 1.543  0.9844

Nyblom stability test
------------------------------------
Joint Statistic:  138.102
Individual Statistics:
mu      0.25575
ar1     0.11380
ma1     0.11365
omega  12.86315
alpha1  0.10283
beta1   0.07074

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           0.5307 0.5957605    
Negative Sign Bias  3.4569 0.0005671 ***
Positive Sign Bias  2.1905 0.0286975  **
Joint Effect       16.7883 0.0007812 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     62.06    1.816e-06
2    30     65.61    1.180e-04
3    40     79.80    1.266e-04
4    50     98.70    3.364e-05


Elapsed time : 0.3023829
```

- The Log-likelihood of the model is 2648.301. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

GARCH Model Forecast:

```
> ugfit_IDFCFIRSTB

*---------------------------------*
*          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      0.001015    0.000632   1.606590  0.10814
ar1     0.313060    3.149574   0.099397  0.92082
ma1    -0.315259    3.122533  -0.100963  0.91958
omega   0.000000    0.000001   0.251030  0.80179
alpha1  0.012100    0.001174  10.306437  0.00000
beta1   0.986501    0.001018 968.736047  0.00000
```

The above table shows the forecasted value using the GARCH model for the daily return.

-Estimating EGARCH model for IDFCFIRSTB

```
> egfit_IDFCFIRSTB

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.000826    0.000634      1.3036  0.19238
ar1     0.524177    0.079579      6.5869  0.00000
ma1    -0.523188    0.079586     -6.5738  0.00000
omega   0.000887    0.000614      1.4448  0.14852
alpha1 -0.006000    0.005591     -1.0732  0.28320
beta1   1.000000    0.000002 439784.9577  0.00000
gamma1  0.034069    0.000460     74.0202  0.00000

Robust Standard Errors:
        Estimate  Std. Error     t value Pr(>|t|)
mu      0.000826    0.000666  1.2394e+00  0.21520
ar1     0.524177    0.015029  3.4878e+01  0.00000
ma1    -0.523188    0.014600 -3.5835e+01  0.00000
omega   0.000887    0.000987  8.9875e-01  0.36879
alpha1 -0.006000    0.009046 -6.6327e-01  0.50716
beta1   1.000000    0.000004  2.6534e+05  0.00000
gamma1  0.034069    0.000849  4.0112e+01  0.00000

LogLikelihood : 2650.802
```

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

Akaike       -4.7550
Bayes        -4.7235
Shibata      -4.7551
Hannan-Quinn -4.7431

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.001043  0.9742
Lag[2*(p+q)+(p+q)-1][5]  0.244751  1.0000
Lag[4*(p+q)+(p+q)-1][9]  2.438360  0.9571
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      29.06 7.034e-08
Lag[2*(p+q)+(p+q)-1][5]     29.34 4.861e-08
Lag[4*(p+q)+(p+q)-1][9]     30.18 3.908e-07
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]  0.005448 0.500 2.000  0.9412
ARCH Lag[5]  0.288521 1.440 1.667  0.9433
ARCH Lag[7]  0.356311 2.315 1.543  0.9895
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  1.1979
Individual Statistics:
mu     0.28332
ar1    0.07426
ma1    0.07434
omega  0.04740
alpha1 0.09496
beta1  0.04533
gamma1 0.14247

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           0.4425 0.6582401
Negative Sign Bias  3.4541 0.0005731 ***
Positive Sign Bias  2.4124 0.0160098  **
Joint Effect       17.7853 0.0004871 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     62.71    1.430e-06
2    30     70.63    2.488e-05
3    40     75.70    3.864e-04
4    50     92.14    1.885e-04


Elapsed time : 0.6666691
```

- The Log-likelihood of the model is 2650.808. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be

rejected and hence the observed values and expected values do not differ by a lot.

-EGARCH FORECAST IDFCFIRSTB

```
> egforecast_IDFCFIRSTB

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

0-roll forecast [T0=2024-09-27]:
        Series   Sigma
T+1  0.0008313 0.01462
T+2  0.0008287 0.01463
T+3  0.0008274 0.01463
T+4  0.0008266 0.01464
T+5  0.0008263 0.01465
T+6  0.0008261 0.01465
T+7  0.0008260 0.01466
T+8  0.0008259 0.01467
T+9  0.0008259 0.01467
T+10 0.0008259 0.01468
```

The result of forecasting is shown in Figure . The results show that the returns are positive for the next 10 days, with a mean value of 0.08% and a standard deviation of 1.4%.

WEEKLY RETURNS

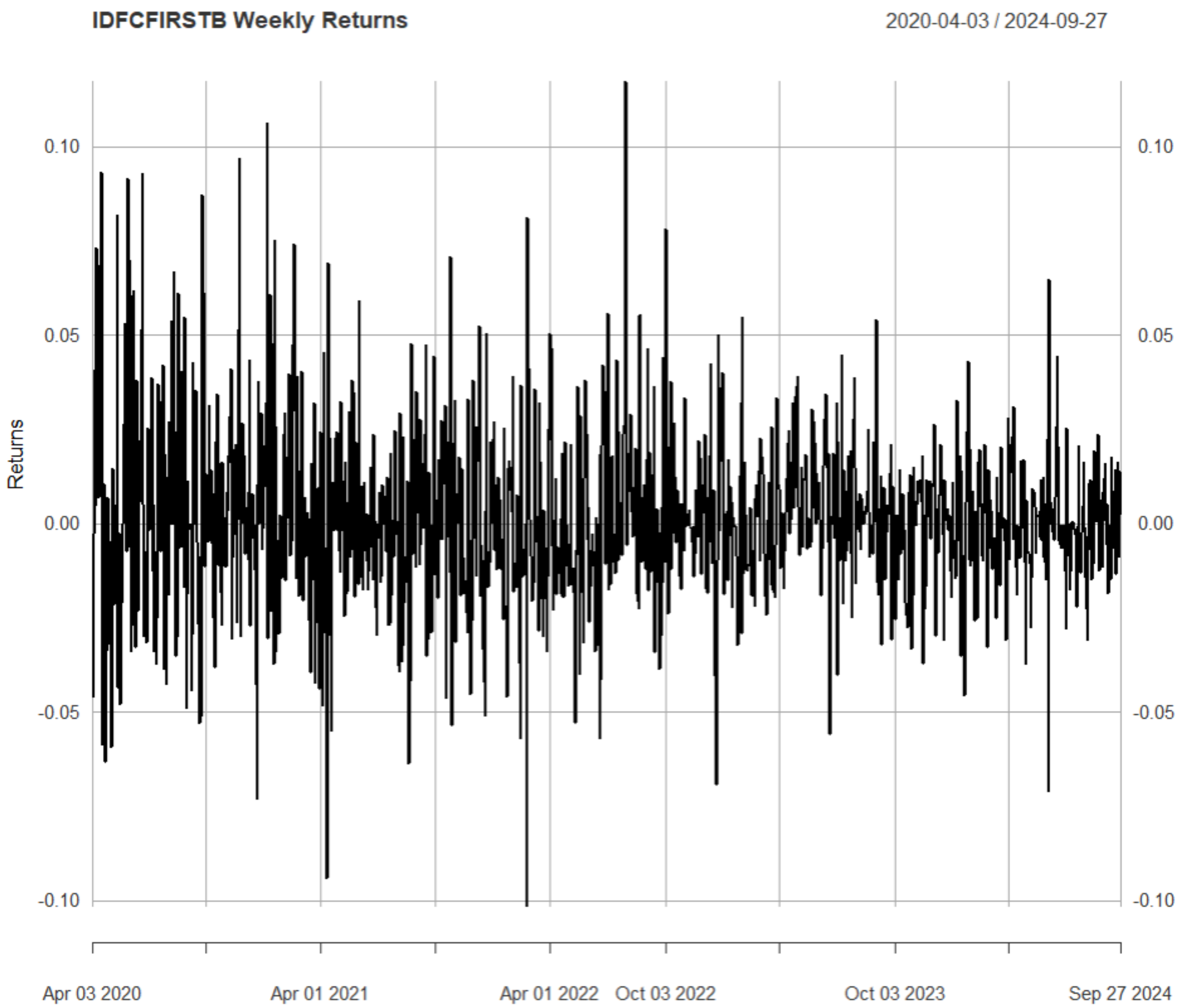
```
Call:
lm(formula = IDFCFIRSTB.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
      Min        1Q    Median        3Q       Max
-0.147283 -0.024075 -0.003689  0.019723  0.209132

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.004090   0.003324   1.230     0.22
NSEI.ExcessReturns 1.170559   0.131207   8.921 2.53e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04537 on 206 degrees of freedom
Multiple R-squared:  0.2787,	Adjusted R-squared:  0.2752
F-statistic: 79.59 on 1 and 206 DF,  p-value: 2.529e-16
```

CAPEM:

Weekly Returns (Beta = 1.171)

Interpretation:

Beta of 1.171 Weekly, which suggests that the sensitivity of this stock towards market trends is somewhat lower in comparison to a weekly scale but the values are still higher than the market. When the market has shifted by 1%, the stock has moved by 1.171%. This shows moderate volatility during a week, which is pretty manageable for risk-exposed investors looking to balance risk.

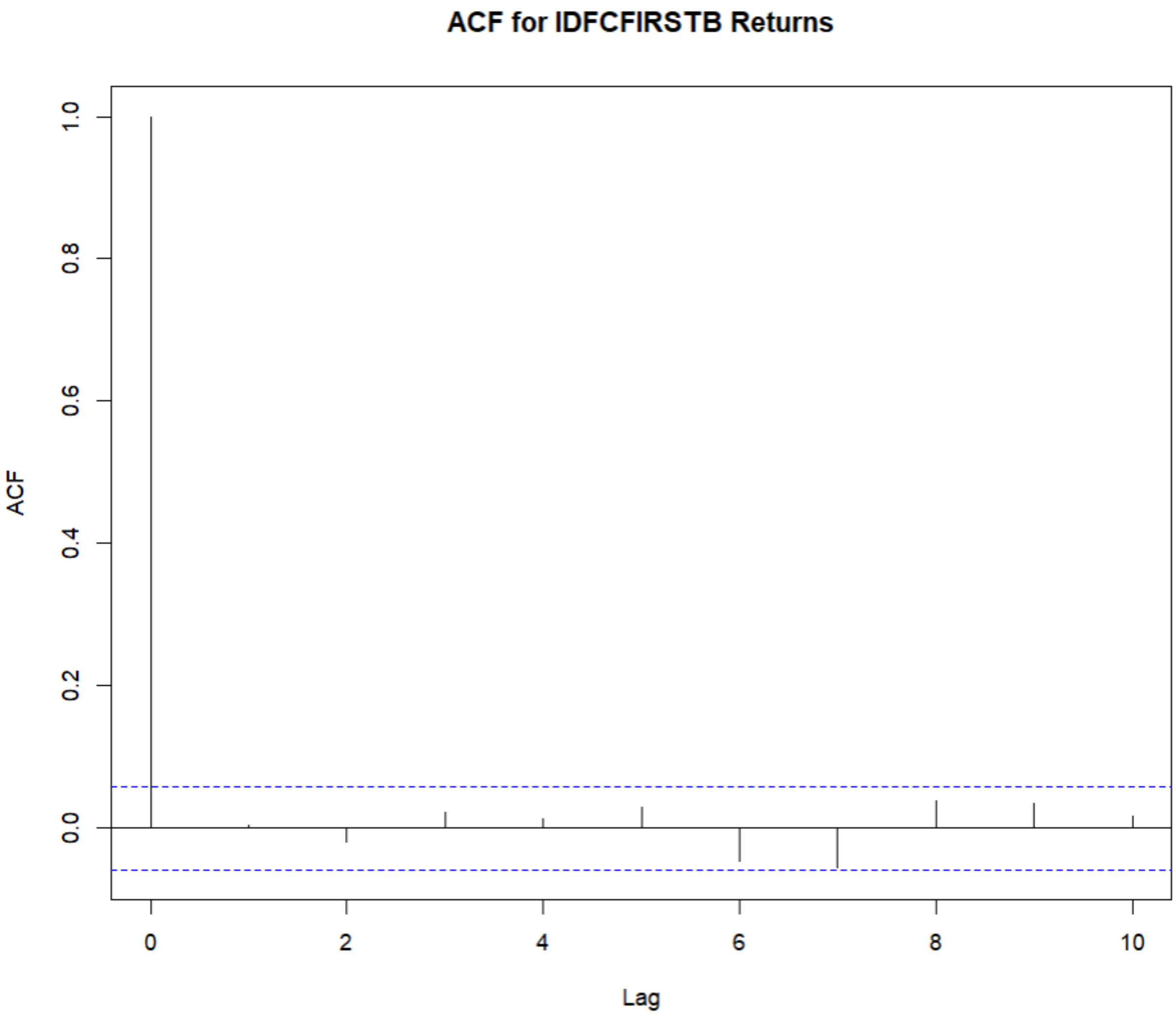


Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01 which is less than 0.05 or 5%. The experiments yielded the following results :

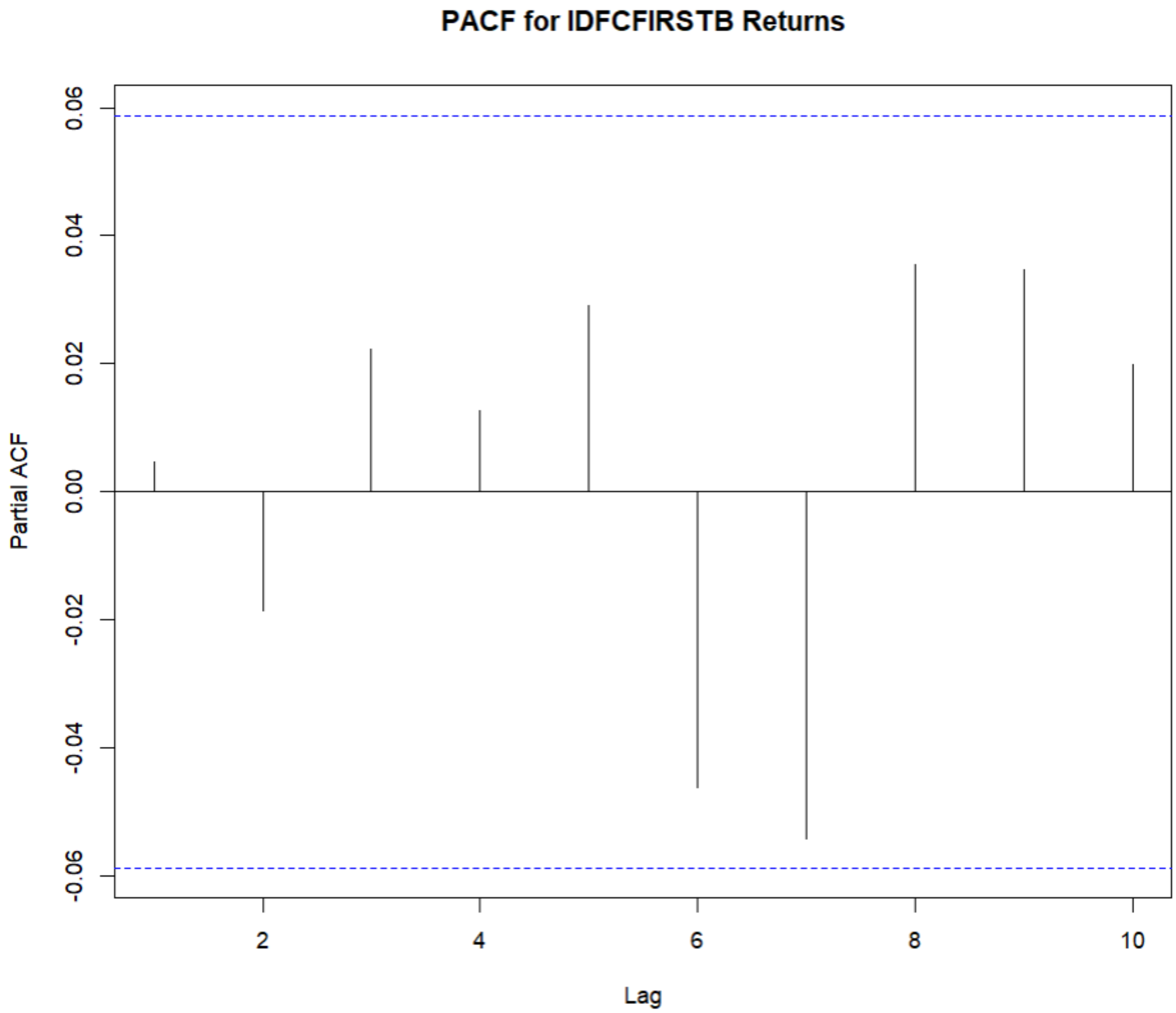
```
> adf.test(returns_IDFCFIRSTB, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  returns_IDFCFIRSTB
Dickey-Fuller = -9.244, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot:



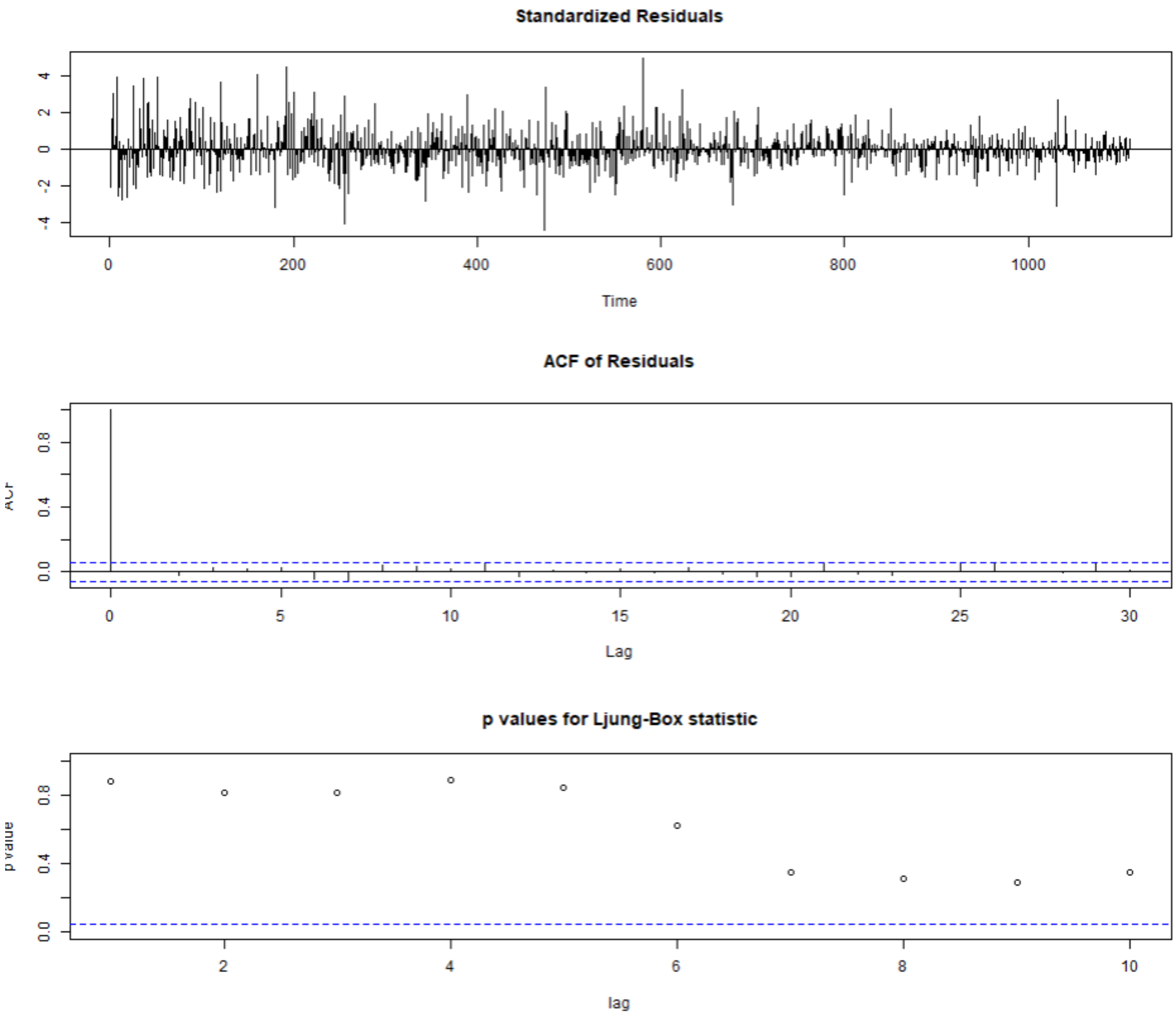
Most of the lags have values within the confidence interval, suggesting no significant partial correlation. Few lags have PACF values outside the confidence interval, indicating statistically significant partial correlations. Based on the analysis, AR(1) is a significant model that can be considered for this plot.

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IDFCFIRSTB)

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

Coefficients:
      intercept
         0.0014
s.e.     0.0007

sigma^2 estimated as 0.0005522:  log likelihood = 2590.73,  aic = -5177.46
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IDFCFIRSTB
     Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
1112    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1113    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1114    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1115    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1116    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1117    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1118    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1119    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1120    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
1121    0.001427881 -0.02868629 0.03154206 -0.04462778 0.04748354
```

GARCH & EGARCH:

-Weekly Garch

```
> 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
```

- We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.

- Now we can start by running the EGARCH model on the daily returns of e-GARCH Model.

-Weekly 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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

-GARCH MODEL FITTING

```
> ugfit_IDFCFIRSTB

*---------------------------------*
*          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      0.004151    0.003828   1.0843  0.27821
ar1     0.874074    0.133560   6.5444  0.00000
ma1    -0.831935    0.150369  -5.5326  0.00000
omega   0.000000    0.000009   0.0000  1.00000
alpha1  0.026279    0.018841   1.3948  0.16307
beta1   0.967595    0.018499  52.3063  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.004151    0.004219  0.98390  0.32517
ar1     0.874074    0.111864  7.81372  0.00000
ma1    -0.831935    0.132844 -6.26247  0.00000
omega   0.000000    0.000004  0.00000  1.00000
alpha1  0.026279    0.037834  0.69459  0.48731
beta1   0.967595    0.036302 26.65405  0.00000

LogLikelihood : 382.0981

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

Akaike       -3.1873
Bayes        -3.0992
Shibata      -3.1885
Hannan-Quinn -3.1518
```

```
Sign Bias Test
------------------------------------
                    t-value     prob sig
Sign Bias           0.09755 0.922376
Negative Sign Bias  1.34085 0.181287
Positive Sign Bias  3.00742 0.002926 ***
Joint Effect       11.83766 0.007960 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     15.36      0.69972
2    30     31.20      0.35590
3    40     56.88      0.03206
4    50     70.78      0.02252


Elapsed time : 0.3160479
```

Observations from the Diagnostic test for the GARCH model for Weekly Returns

● The resulting log-likelihood of the model is 382.0981.

● GARCH(1,1) and corresponding ARFIMA(1,0,1) are best for weekly returns.

● The ALPHA and Omega parameters are derived by a fitting process of the GARCHmodel. The model's minimal AIC and BIC values are used to describe best fit.

-EGARCH MODEL FITTING

```
> egfit_IDFCFIRSTB

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001845    0.004181  0.44122 0.659051
ar1     0.738686    0.198681  3.71795 0.000201
ma1    -0.620252    0.231445 -2.67991 0.007364
omega  -3.798878    1.417295 -2.68037 0.007354
alpha1  0.055799    0.106682  0.52304 0.600944
beta1   0.373754    0.232664  1.60641 0.108184
gamma1  0.770632    0.183370  4.20261 0.000026

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001845    0.003967  0.46505 0.641898
ar1     0.738686    0.261578  2.82396 0.004743
ma1    -0.620252    0.279870 -2.21622 0.026677
omega  -3.798878    2.236209 -1.69880 0.089356
alpha1  0.055799    0.120697  0.46231 0.643860
beta1   0.373754    0.370920  1.00764 0.313627
gamma1  0.770632    0.232335  3.31690 0.000910

LogLikelihood : 385.5591

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

Akaike       -3.2081
Bayes        -3.1054
Shibata      -3.2098
Hannan-Quinn -3.1667
```

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      0.853  0.3557
Lag[2*(p+q)+(p+q)-1][5]     2.118  0.9318
Lag[4*(p+q)+(p+q)-1][9]     5.767  0.2965
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.07075  0.7903
Lag[2*(p+q)+(p+q)-1][5]   0.82485  0.8979
Lag[4*(p+q)+(p+q)-1][9]   4.69848  0.4750
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.05077 0.500 2.000  0.8217
ARCH Lag[5]   0.58981 1.440 1.667  0.8568
ARCH Lag[7]   4.86534 2.315 1.543  0.2385

Nyblom stability test
------------------------------------
Joint Statistic:  2.322
Individual Statistics:
mu     0.08836
ar1    0.11948
ma1    0.06172
omega  1.22625
alpha1 0.11890
beta1  1.25423
gamma1 0.24017

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          0.11189 0.9110
Negative Sign Bias 0.10848 0.9137
Positive Sign Bias 0.15348 0.8782
Joint Effect       0.03637 0.9982


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     23.49       0.2164
2    30     28.92       0.4695
3    40     38.92       0.4737
4    50     56.37       0.2186


Elapsed time : 0.2235501
```

- The log-likelihood of the model stands at 385.5591. For IDFCFIRSTB returns, the optimal models identified are eGARCH(1,1) coupled with ARFIMA(1,0,1).
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-GARCHE FORECASTING

```
> ugforecast_IDFCFIRSTB

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

0-roll forecast [T0=2024-09-29]:
       Series   Sigma
T+1  0.003096 0.02750
T+2  0.003228 0.02742
T+3  0.003345 0.02733
T+4  0.003446 0.02725
T+5  0.003535 0.02717
T+6  0.003612 0.02708
T+7  0.003680 0.02700
T+8  0.003740 0.02692
T+9  0.003791 0.02684
T+10 0.003837 0.02675
```

The above table shows the forecasted value using the GARCH model for the daily return.

-EGARCHE FORECASTING

```
> egforecast_IDFCFIRSTB

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

0-roll forecast [T0=2024-09-29]:
        Series   Sigma
T+1   0.002385 0.03288
T+2   0.002244 0.04176
T+3   0.002140 0.04567
T+4   0.002063 0.04722
T+5   0.002006 0.04781
T+6   0.001964 0.04803
T+7   0.001933 0.04812
T+8   0.001910 0.04815
T+9   0.001893 0.04816
T+10  0.001880 0.04817
```

The result of forecasting is shown in Figure. The results show that the returns will mostly be positive on average for the next 10 days, with a mean value of 0.18% and a standard deviation of 4.5%.

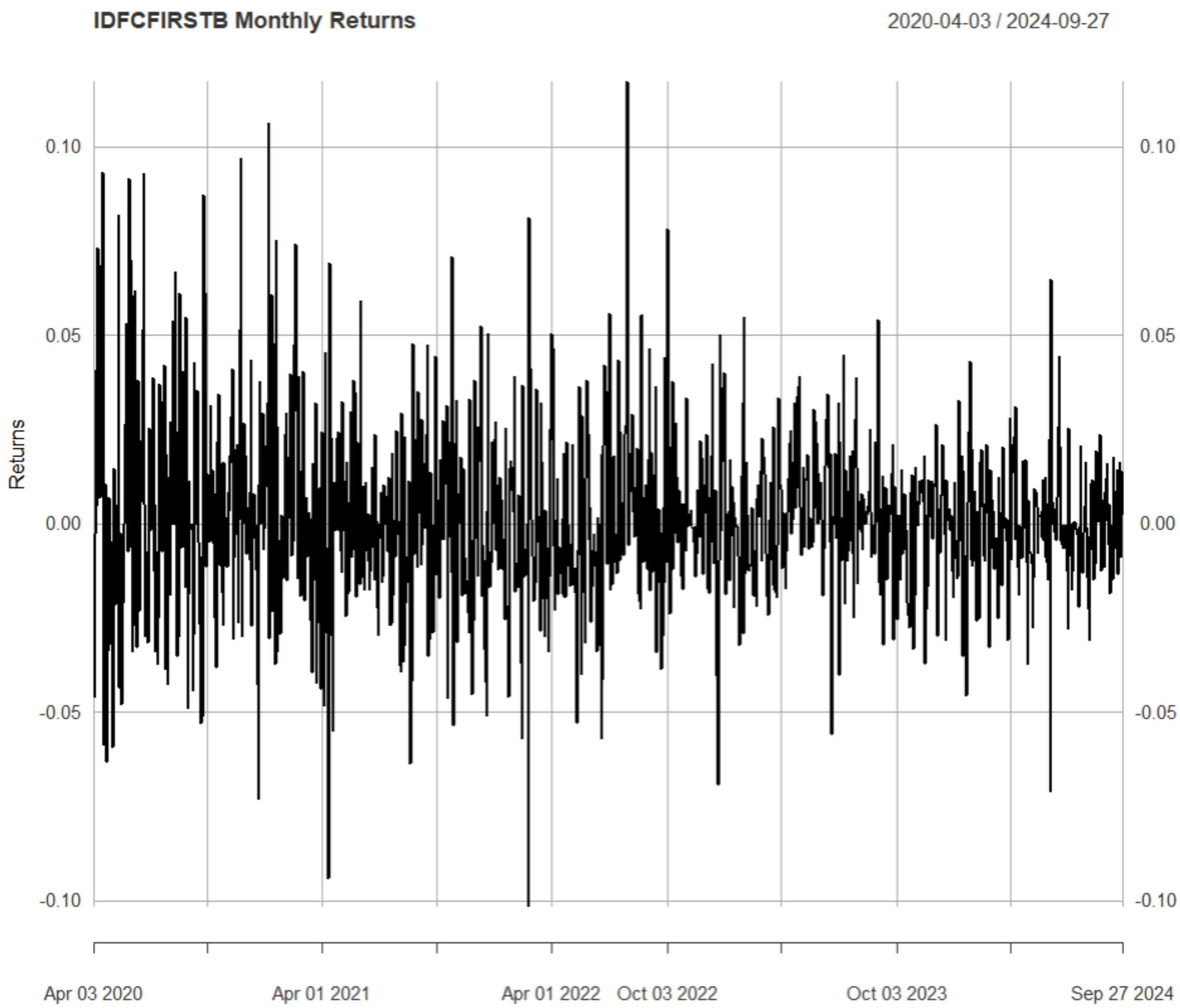
MONTHLY

```
CAPM Regression Results for IDFCFIRSTB.NS

Call:
lm(formula = exStock ~ exNSE, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.27917 -0.06002 -0.01318  0.06494  0.28423 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.02707    0.04105   0.659    0.512    
exNSE        1.04459    0.09438  11.067 2.15e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1016 on 53 degrees of freedom
Multiple R-squared:  0.698,	Adjusted R-squared:  0.6923 
F-statistic: 122.5 on 1 and 53 DF,  p-value: 2.154e-15
```

CAPEM

Monthly Returns (Beta = 1.045)

Interpretation:
A monthly beta of 1.045 aligns the stock closely with the market over a longer timeframe. This implies that IDFC FIRST Bank’s performance is proportionate to the market in the long term, making it less risky for long-term investors compared to its daily and weekly behavior.



B. Estimating AR and MA coefficient using ARIMA model

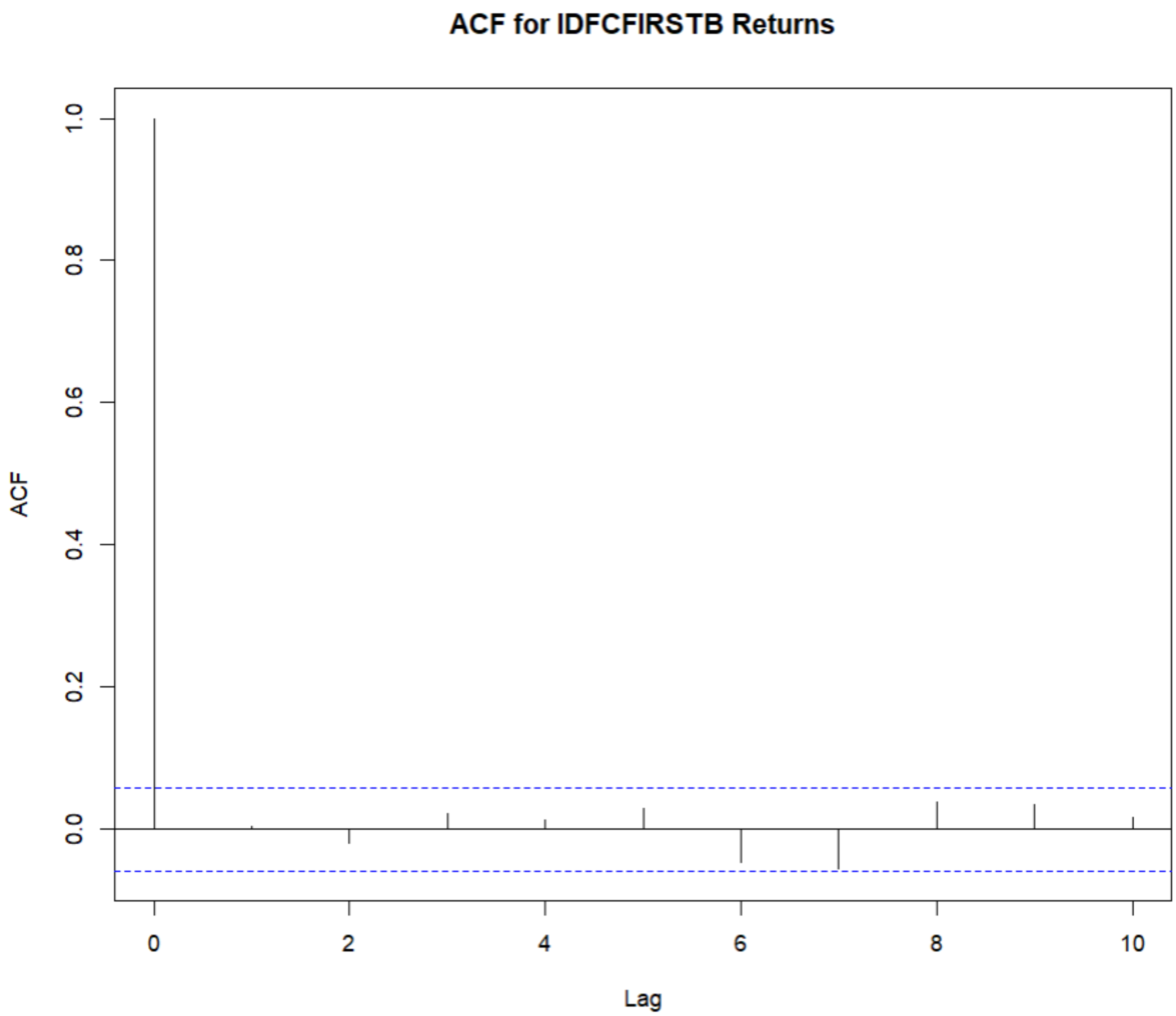
The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary.The p – value from the Augmented Dickey-Fuller Test is less than 0.05 which shows that the series is stationary.

The experiments yielded the following results:

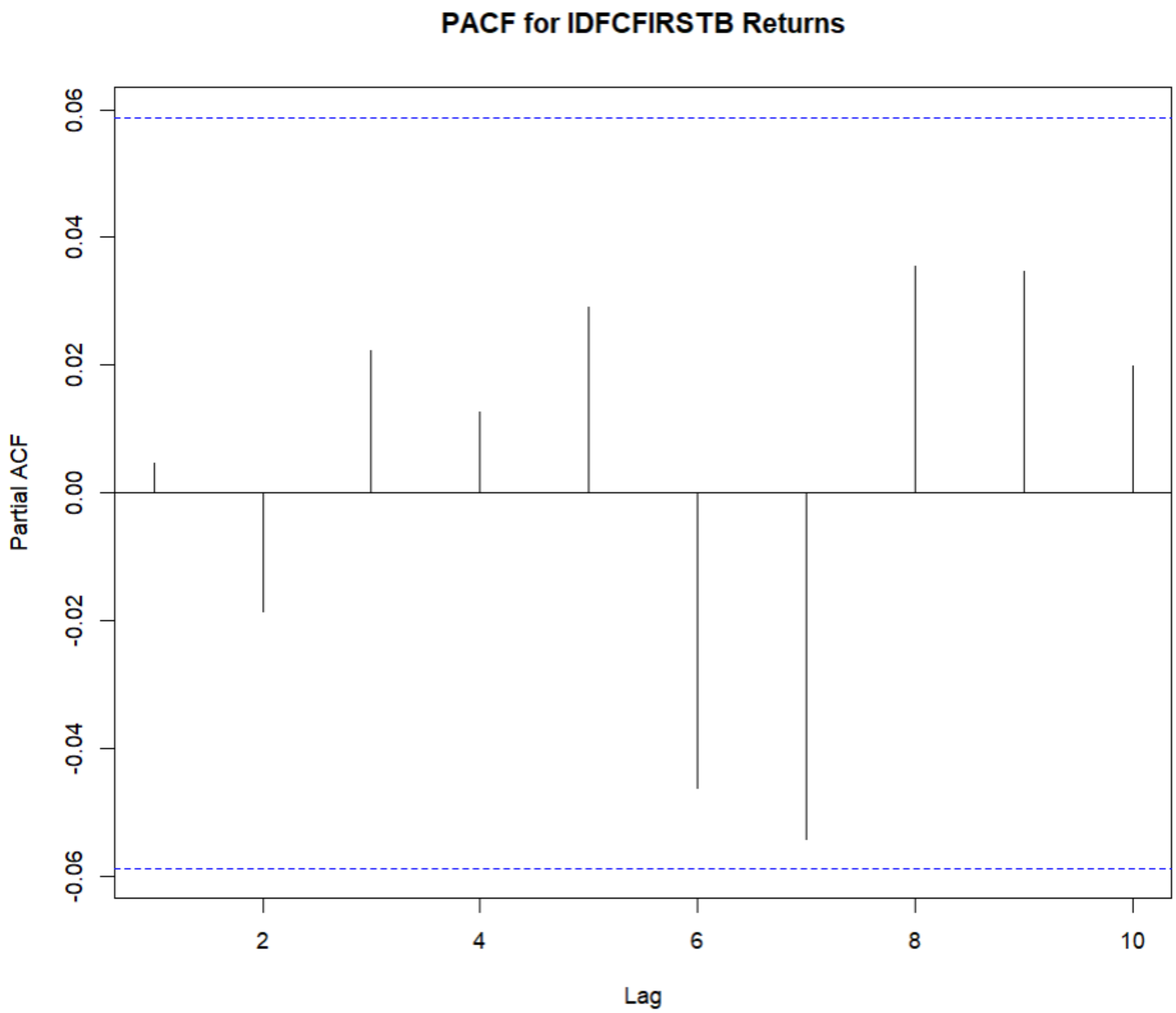
```
        Augmented Dickey-Fuller Test

data:  returns_IDFCFIRSTB
Dickey-Fuller = -9.244, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot :



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot :



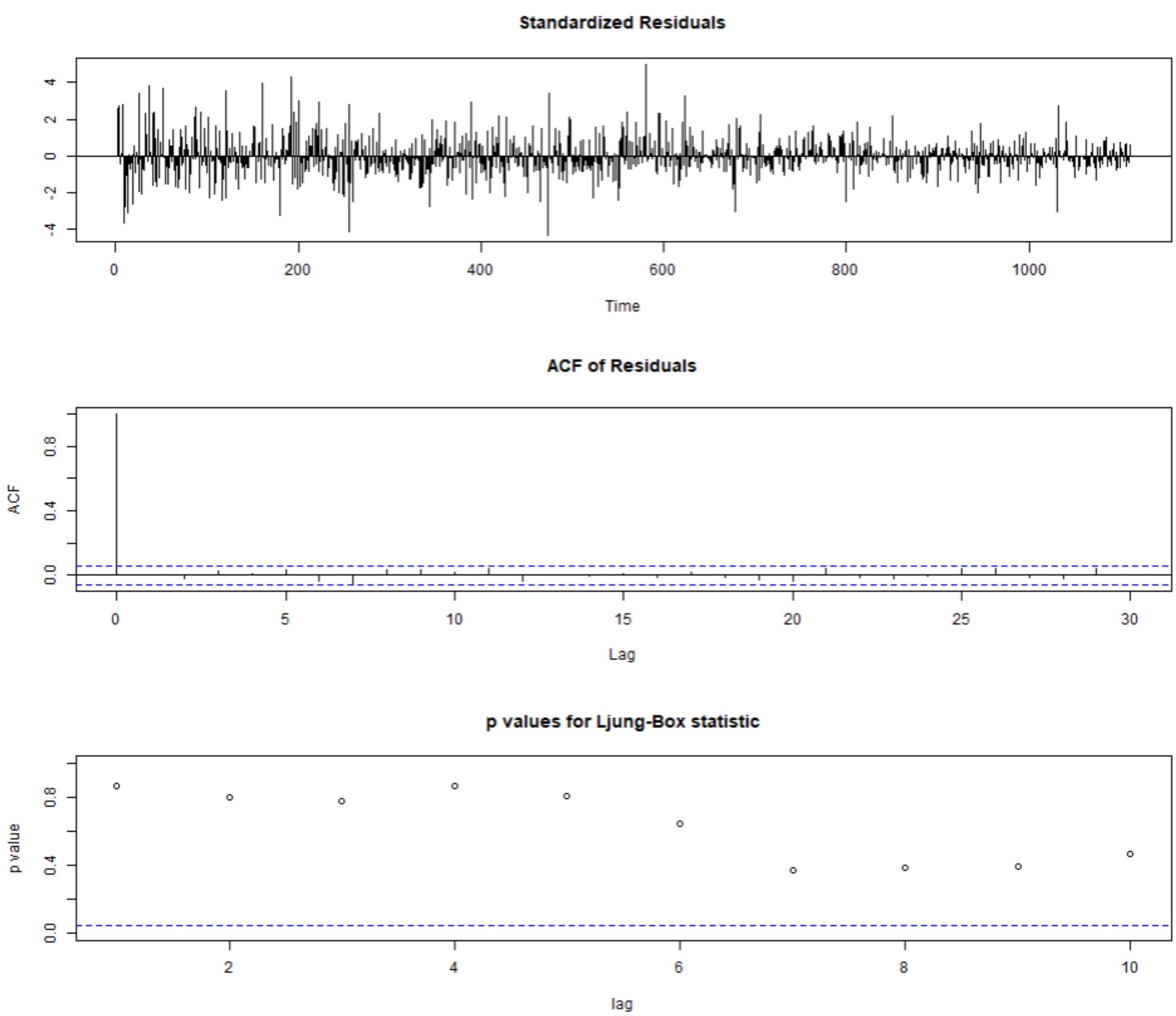
Based on the PACF plot, all lags appear to have autocorrelation values within the confidence intervals, indicating that they are statistically insignificant. The order of the autoregressive model can be taken as AR(0) since the time series data does not depend on past data.

```
> summary(arima_final_IDFCFIRSTB)

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

Coefficients:
      intercept
         0.0014
s.e.     0.0007

sigma^2 estimated as 0.0005522:  log likelihood = 2590.73,  aic = -5177.46
```

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test :



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

GARCH & EGARCHE:

-GARCHE MODEL FIT

```
> ugfit_IDFCFIRSTB

*---------------------------------*
*          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      0.026972    0.016145  1.670565 0.094808
ar1    -0.693191    0.167957 -4.127205 0.000037
ma1     0.881351    0.105944  8.319048 0.000000
omega   0.000000    0.000092  0.000001 1.000000
alpha1  0.000001    0.019070  0.000056 0.999956
beta1   0.992669    0.021858 45.413496 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.026972    0.021963   1.228061 0.219424
ar1    -0.693191    0.190975  -3.629757 0.000284
ma1     0.881351    0.075084  11.738233 0.000000
omega   0.000000    0.000012   0.000004 0.999997
alpha1  0.000001    0.009607   0.000110 0.999912
beta1   0.992669    0.005747 172.742444 0.000000

LogLikelihood : 44.39011
```

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

Akaike       -1.4219
Bayes        -1.2009
Shibata      -1.4434
Hannan-Quinn -1.3366

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.002052  0.9639
Lag[2*(p+q)+(p+q)-1][5]  0.903259  1.0000
Lag[4*(p+q)+(p+q)-1][9]  1.963426  0.9860
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      5.157 0.02316
Lag[2*(p+q)+(p+q)-1][5]     7.559 0.03787
Lag[4*(p+q)+(p+q)-1][9]    10.104 0.04765
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.562 0.500 2.000  0.2113
ARCH Lag[5]     4.030 1.440 1.667  0.1712
ARCH Lag[7]     5.255 2.315 1.543  0.2000

Nyblom stability test
------------------------------------
Joint Statistic:  5.4357
Individual Statistics:
mu     0.2129
ar1    0.1757
```

```
ma1    0.1525
omega  0.1880
alpha1 0.1743
beta1  0.2204

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            2.776 0.0077744 ***
Negative Sign Bias   1.401 0.1673947
Positive Sign Bias   3.573 0.0008039 ***
Joint Effect        14.751 0.0020426 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     18.59       0.4832
2    30     29.33       0.4478
3    40     36.37       0.5905
4    50     47.85       0.5197


Elapsed time : 0.073071
```

- The Log-likelihood of the model is 44.3901. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-EGARCHE MODEL FIT

```
> egfit_IDFCFIRSTB

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.026695    0.010192  2.61933 0.008810
ar1    -0.756501    0.084360 -8.96749 0.000000
ma1     0.927131    0.041286 22.45608 0.000000
omega  -3.752862    1.886612 -1.98921 0.046678
alpha1  0.265573    0.183367  1.44831 0.147530
beta1   0.171248    0.414989  0.41266 0.679858
gamma1  0.300005    0.324628  0.92415 0.355408

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.026695    0.007998   3.3376 0.000845
ar1    -0.756501    0.045641 -16.5750 0.000000
ma1     0.927131    0.017637  52.5680 0.000000
omega  -3.752862    0.670481  -5.5973 0.000000
alpha1  0.265573    0.122156   2.1741 0.029701
beta1   0.171248    0.152759   1.1210 0.262274
gamma1  0.300005    0.221118   1.3568 0.174856

LogLikelihood : 45.99445

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

Akaike       -1.4442
Bayes        -1.1864
Shibata      -1.4730
Hannan-Quinn -1.3448
```

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1048  0.7462
Lag[2*(p+q)+(p+q)-1][5]    1.3967  0.9992
Lag[4*(p+q)+(p+q)-1][9]    2.4467  0.9564
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.3851  0.5349
Lag[2*(p+q)+(p+q)-1][5]    3.2245  0.3676
Lag[4*(p+q)+(p+q)-1][9]    6.6732  0.2281
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.078 0.500 2.000 0.29919
ARCH Lag[5]     5.215 1.440 1.667 0.09165
ARCH Lag[7]     6.831 2.315 1.543 0.09442

Nyblom stability test
------------------------------------
Joint Statistic:  1.1111
Individual Statistics:
mu     0.2871
ar1    0.1874
ma1    0.1674
omega  0.4253
alpha1 0.0685
beta1  0.4294
gamma1 0.1376

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           1.1844 0.2420
Negative Sign Bias  0.9114 0.3665
Positive Sign Bias  0.3249 0.7467
Joint Effect        1.6302 0.6526


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     17.85       0.5324
2    30     29.33       0.4478
3    40     28.96       0.8799
4    50     47.85       0.5197


Elapsed time : 0.1651371
```

- The Log-likelihood of the model is 45.9945. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-GARCHE FORECASTING

```
> ugforecast_IFBIND

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

0-roll forecast [T0=2024-08-31]:
      Series  Sigma
T+1  0.05943 0.1386
T+2  0.03495 0.1386
T+3  0.04777 0.1385
T+4  0.04106 0.1385
T+5  0.04457 0.1384
T+6  0.04273 0.1384
T+7  0.04369 0.1383
T+8  0.04319 0.1383
T+9  0.04345 0.1383
T+10 0.04332 0.1382
```

The above table shows the forecasted value using the GARCH model for the daily return.

-EGARCHE FORECASTING

```
> egforecast_IFBIND

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

0-roll forecast [T0=2024-08-31]:
      Series  Sigma
T+1   0.08459 0.1943
T+2   0.02569 0.1886
T+3   0.06004 0.1836
T+4   0.04001 0.1793
T+5   0.05169 0.1756
T+6   0.04488 0.1724
T+7   0.04885 0.1696
T+8   0.04653 0.1672
T+9   0.04789 0.1650
T+10  0.04710 0.1632
```

The result of forecasting is shown in Figure . The results show that the returns fluctuate for the next 10 days, with a mean value of 4.19% and a standard deviation of 16.1%.

Calculating Value at Risk For IDFC:-

Value at Risk (VaR) calculates the possible decline in the value of an investment or portfolio over a given period of time, assuming a particular degree of confidence (e.g., 95% or 99%).It helps investors and institutions comprehend the worst-case scenario under typical market conditions by giving them a measurable indicator of downside risk.

Above is the graph for IDFCFIRSTB, showing the value at risk at different confidence intervals from 75% to 100%. At 75% confidence level, VaR is 300, which means that there is only a 25% chance that the stock price will fall by 300 rupees in a day. Similarly, at 100% confidence level, there is no chance that the stock price will fall by more than 1,000 rupees.

IFBIND(Indian Fine Blanks Limited)

IFB
Industries Limited

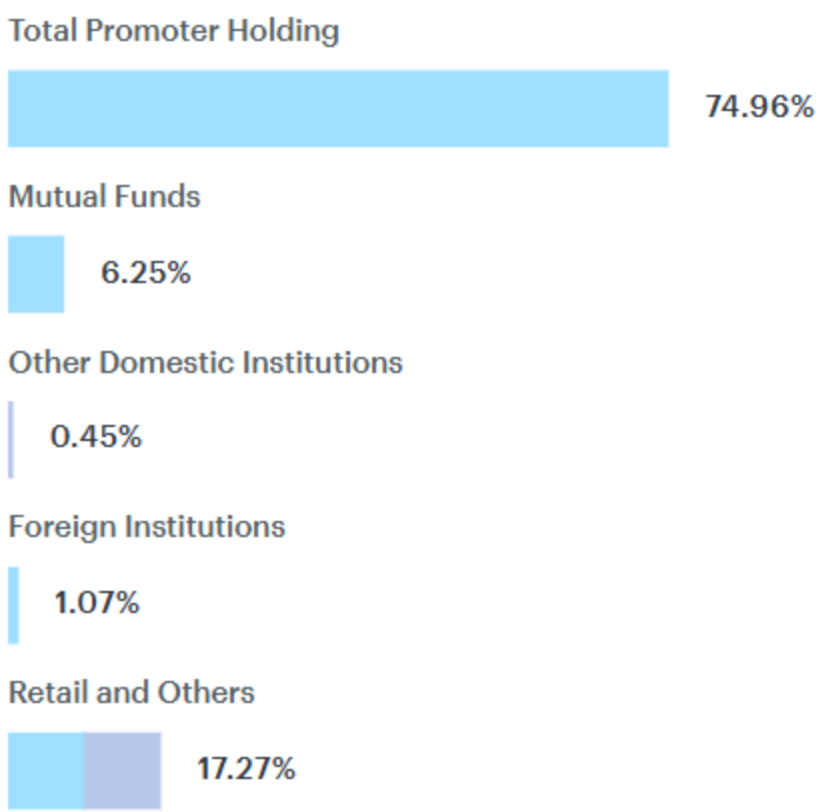
About the company

1.1.1 Nature of the business

IFB Industries Limited, initially known as Indian Fine Blanks Limited, specializes in fine blanking, a precision metal forming process. The company has expanded into various segments including engineering, home appliances, and motors for white goods and automotive applications. IFB is widely recognized for its high-quality home appliances such as washing machines, microwaves, dishwashers, and kitchen solutions

1.1.2 Ownership category

IFB Industries is a publicly traded company listed on the Bombay Stock Exchange (BSE) and the National Stock Exchange of India (NSE). It is part of a group that also includes IFB Agro, which operates in the alcohol and processed foods sector



IFBIND Shareholding pattern

1.1.3 When did it start?

The company was founded in 1974, with operations starting in collaboration with Heinrich Schmid AG of Switzerland. IFB began with a focus on fine blanking technology in Kolkata and later expanded its engineering and appliance divisions

1.1.4. Significance in the industry

IFB Industries is a key player in India's home appliances market, holding a strong presence with a wide distribution network and customer base. The company has achieved a market share of 60% in the fine blanking segment in India. In addition, its home appliance segment, especially in washing machines and kitchen appliances, is well-regarded for innovation and qualit

1.1.5. Overall greatness of the company

IFB Industries has established itself as a leader in both the engineering and home appliance sectors in India. Its commitment to quality, innovation, and customer satisfaction has solidified its reputation over the decades. The company continues to expand its product lines and invest in new technologies to cater to the growing demand in domestic and international markets.

DAILY RETURNS

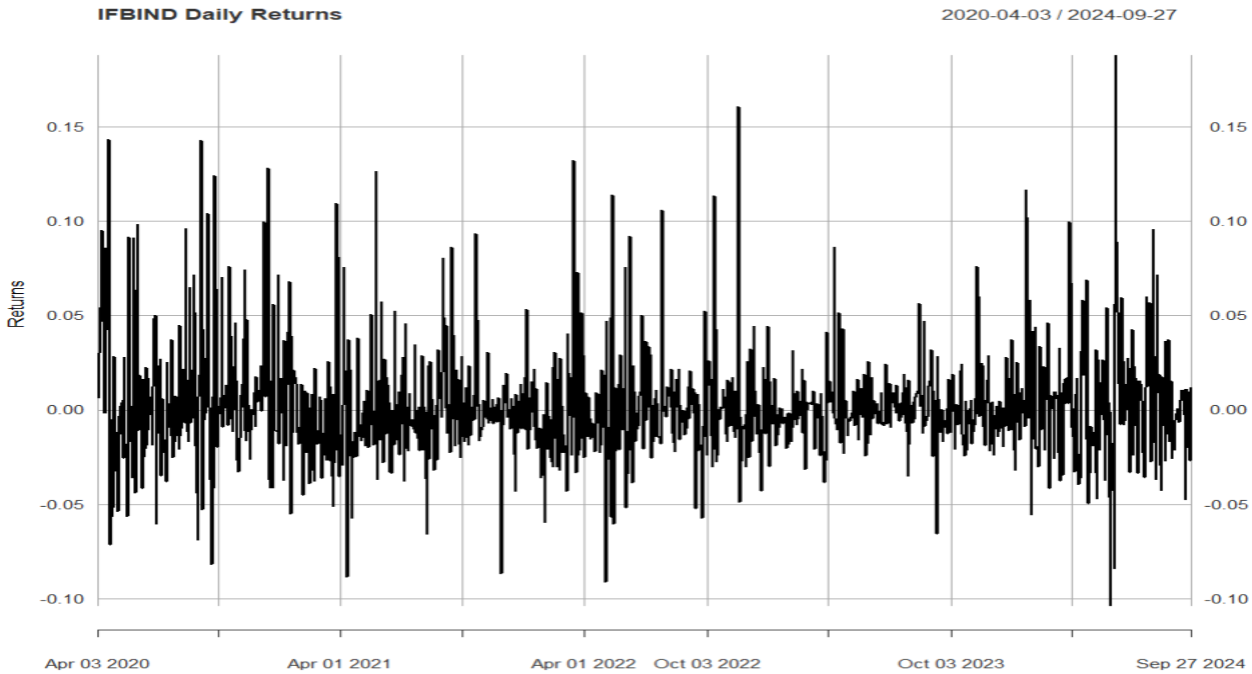
CAPM

```
Call:
lm(formula = IFBIND.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.091894 -0.014620 -0.004331  0.008841  0.160165 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)        -0.0004544  0.0013229  -0.344    0.731    
NSEI.ExcessReturns  0.8581418  0.0791215  10.846   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02793 on 967 degrees of freedom
Multiple R-squared:  0.1085,	Adjusted R-squared:  0.1075 
F-statistic: 117.6 on 1 and 967 DF,  p-value: < 2.2e-16
```

Daily Returns (Beta = 0.858)

Interpretation:

IFBIND is far less volatile than the market on a daily basis, considering the beta stands at 0.858. The returns of the stock move



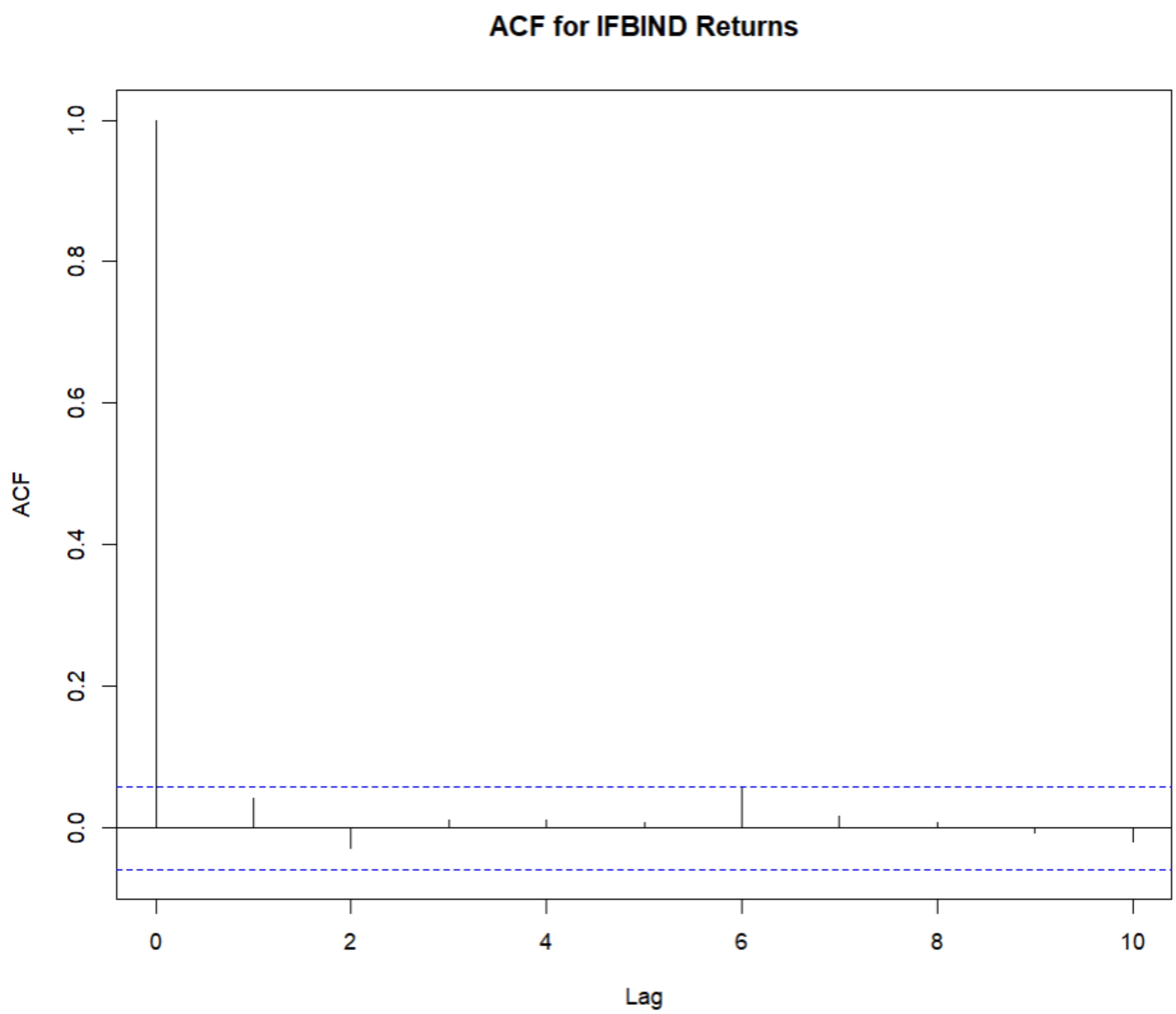
B. Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots. An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01, which is less than 0.05 or 5%. Hence, the series is stationary and rejects the null hypothesis. The experiments yielded the following results:

```
        Augmented Dickey-Fuller Test

data:  returns_IFBIND
Dickey-Fuller = -10.922, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

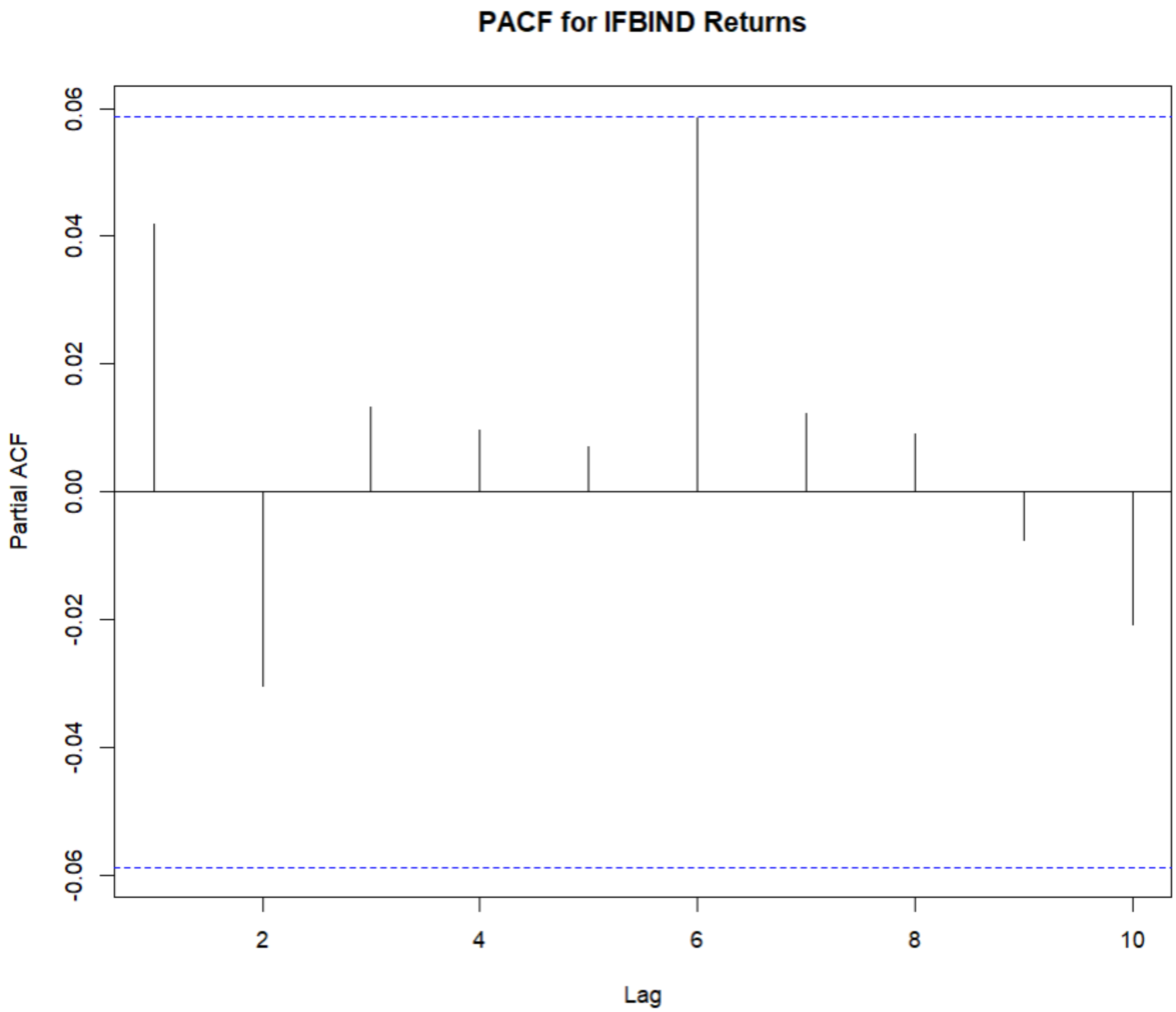
ACF Plot:



The ACF property specifies a unique autocorrelation sequence.All subsequent lags show ACF values that are within the confidence bound.
The ACF decreases exponentially towards zero as the lag (latency) h increases, φ1being positive. When φ1 is negative, the ACF decays exponentially to zero as the latency increases, but the autocorrelations show an alternate sign, oscillating between positive and negative values.At

current, the plot can be categorized under white noise.Based on the lack of significant autocorrelations at any lag, the data can be estimated to fit an MA(0) model.

PACF Plot :



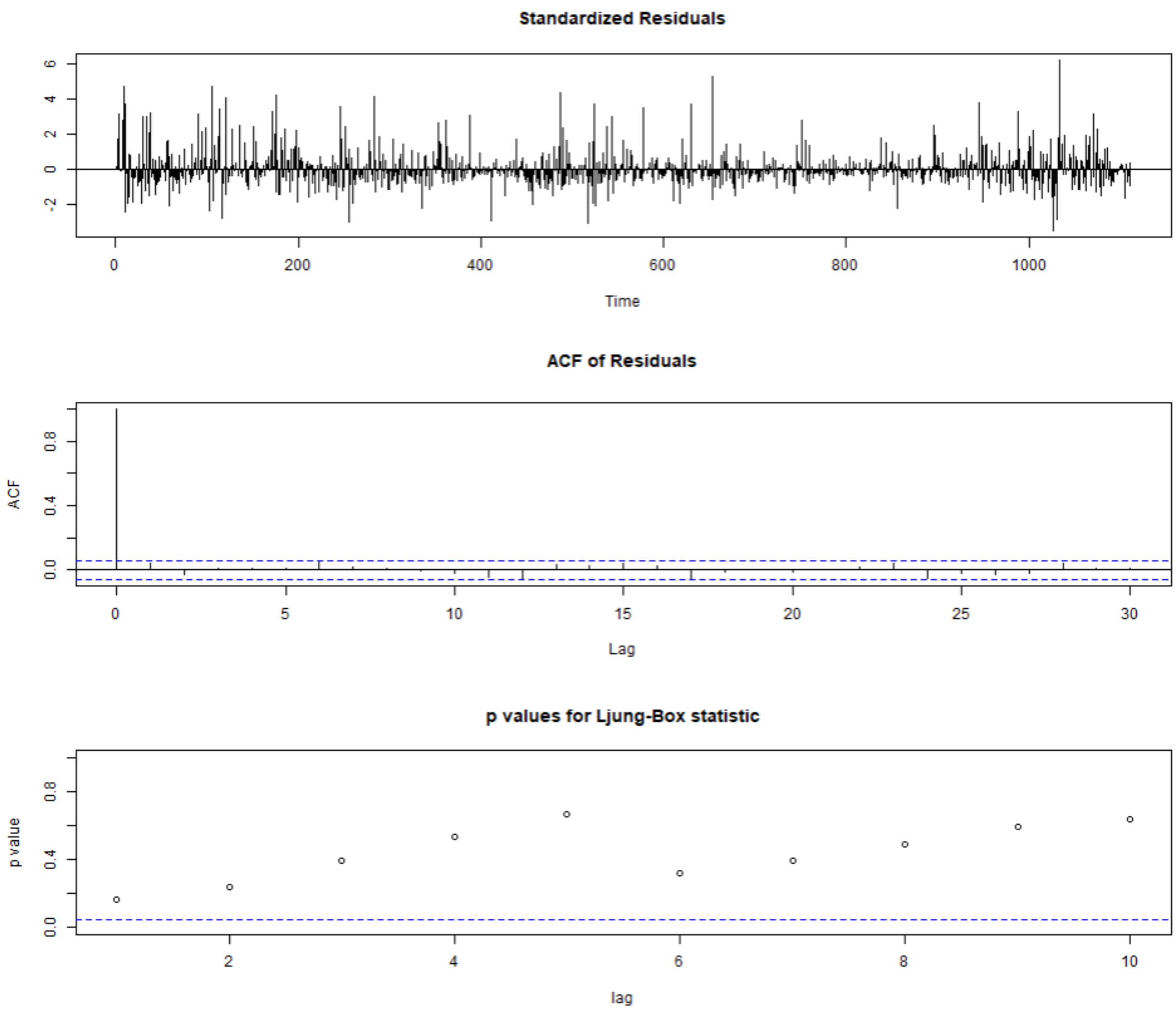
Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero.

Following to this, ARIMA model was run on all the orders(p,d,q). The best model is the one which have the least AIC value.

```
> summary(arima_final_IFBIND)

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

Coefficients:
      intercept
         0.0022
s.e.     0.0009

sigma^2 estimated as 0.0008898:  log likelihood = 2325.7,  aic = -4647.4

Training set error measures:
                        ME       RMSE        MAE  MPE MAPE      MASE      ACF1
Training set -3.758966e-18 0.02982889 0.01993537 -Inf  Inf 0.6996171 0.0418626
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation:

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often smaller than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IFBIND
     Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
1112    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1113    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1114    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1115    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1116    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1117    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1118    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1119    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1120    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1121    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
```

GARCH & EGARCH:

GARCH 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
```

EGarch 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
```

Garch Model Fitting:

```
> ugfit_IFBIND

*---------------------------------*
*          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      0.001476    0.000818   1.8046 0.071141
ar1    -0.891239    0.148815  -5.9889 0.000000
ma1     0.909810    0.133606   6.8097 0.000000
omega   0.000113    0.000030   3.7426 0.000182
alpha1  0.112226    0.025879   4.3366 0.000014
beta1   0.761956    0.051258  14.8651 0.000000
```

```
------------------------------------
                        statistic p-value
Lag[1]                     0.1958  0.6582
Lag[2*(p+q)+(p+q)-1][5]    1.6311  0.9946
Lag[4*(p+q)+(p+q)-1][9]    4.1528  0.6548
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                  0.0006488  0.9797
Lag[2*(p+q)+(p+q)-1][5] 1.8070794  0.6647
Lag[4*(p+q)+(p+q)-1][9] 2.8218673  0.7880
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.8072 0.500 2.000  0.3689
ARCH Lag[5]    1.8963 1.440 1.667  0.4946
ARCH Lag[7]    2.2711 2.315 1.543  0.6600

Sign Bias Test
------------------------------------
                   t-value   prob sig
Sign Bias            1.287 0.1982
Negative Sign Bias   0.965 0.3348
Positive Sign Bias   1.055 0.2914
Joint Effect         2.223 0.5274


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     199.5    4.330e-32
2    30     220.4    2.578e-31
3    40     235.6    6.055e-30
4    50     247.5    2.602e-28


Elapsed time : 0.4148369
```

- The GARCH(1,1) model for IFBIND's daily returns demonstrates strong performance in capturing volatility dynamics. The mean parameter mu (0.001476) is marginally significant (p = 0.071141), indicating a low but consistent positive return.

- The moving average (ma1) term is also significant (0.909810, $p < 0.01$), indicating that past errors play a critical role in predicting current returns. These findings highlight that volatility clustering is a key characteristic of IFBIND's daily returns. Diagnostic tests validate the model's adequacy.
- The Ljung-Box test for standardized and squared residuals shows no significant autocorrelation ($p > 0.05$), confirming that the model adequately captures the dependency structure of returns.

Overall, the GARCH(1,1) model effectively captures the volatility dynamics of IFBIND's daily returns, with significant persistence and sensitivity to past shocks.

EGARCH Model Fitting

```
> egfit_IFBIND

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.000863    0.000395   2.18763 0.028697
ar1    -0.868217    0.032681 -26.56617 0.000000
ma1     0.893196    0.030086  29.68857 0.000000
omega  -0.401968    0.063222  -6.35806 0.000000
alpha1  0.010525    0.017096   0.61568 0.538103
beta1   0.940931    0.009187 102.42455 0.000000
gamma1  0.171172    0.028096   6.09248 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.000863    0.000216   4.00388 0.000062
ar1    -0.868217    0.009233 -94.03016 0.000000
ma1     0.893196    0.011656  76.63039 0.000000
omega  -0.401968    0.061937  -6.49000 0.000000
alpha1  0.010525    0.032390   0.32496 0.745212
beta1   0.940931    0.009521  98.82547 0.000000
gamma1  0.171172    0.053297   3.21168 0.001320
```

```
LogLikelihood : 2392.377

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

Akaike       -4.2902
Bayes        -4.2587
Shibata      -4.2903
Hannan-Quinn -4.2783

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1522  0.6964
Lag[2*(p+q)+(p+q)-1][5]    1.3414  0.9995
Lag[4*(p+q)+(p+q)-1][9]    3.6489  0.7702
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.7919  0.3735
Lag[2*(p+q)+(p+q)-1][5]    2.2371  0.5636
Lag[4*(p+q)+(p+q)-1][9]    2.9195  0.7722
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.5375 0.500 2.000  0.4635
ARCH Lag[5]    1.3893 1.440 1.667  0.6219
ARCH Lag[7]    1.6138 2.315 1.543  0.7983
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  1.6282
Individual Statistics:
mu     0.1418
ar1    0.1395
ma1    0.1500
omega  0.1979
alpha1 0.6994
beta1  0.2007
gamma1 0.1774

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           1.2097 0.2267
Negative Sign Bias  0.8777 0.3803
Positive Sign Bias  1.4988 0.1342
Joint Effect        3.0277 0.3874


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     201.4    1.779e-32
2    30     220.2    2.703e-31
3    40     237.4    2.919e-30
4    50     244.2    1.002e-27


Elapsed time : 0.3389668
```

- The eGARCH(1,1) model for IFBIND's daily returns exhibits strong performance in capturing volatility dynamics, as evidenced by a log-likelihood value of 2392.377 and favorable information criteria (Akaike: -4.2902, Bayes: -4.2587, Shibata: -4.2903).
- The mean parameter (mu) is small but statistically significant (0.000863, p = 0.028697), indicating consistent positive returns
- . The autoregressive term (ar1) is highly significant (-0.868217, p < 0.01) with a negative coefficient, reflecting a substantial influence of past returns on current returns.

- Similarly, the moving average (ma1) term is significant (0.893196, $p < 0.01$), highlighting the importance of past errors in predicting current returns.
- The Ljung-Box tests for standardized and squared residuals show no significant autocorrelation ($p > 0.05$), indicating that the model adequately captures the dependency structure in the returns.

In summary, the eGARCH(1,1) model effectively captures the persistence and asymmetry in the volatility of IFBIND's daily returns.

GARCH Daily Forecasts:

```
> ugforecast_IFBIND

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

0-roll forecast [T0=2024-09-27]:
       Series   Sigma
T+1  0.001921 0.02533
T+2  0.001080 0.02595
T+3  0.001830 0.02648
T+4  0.001162 0.02693
T+5  0.001757 0.02733
T+6  0.001226 0.02766
T+7  0.001699 0.02796
T+8  0.001278 0.02821
T+9  0.001653 0.02843
T+10 0.001319 0.02862
```

The sGARCH daily forecast for IFBIND predicts stable and small positive returns over the next 10 days, with values starting at **0.001921** and gradually decreasing to **0.001319**. The forecasted volatility (sigma) increases slightly from **0.02533** on day 1 to **0.02862** by day 10, indicating a slight rise in uncertainty. Overall, the model suggests steady returns with minimal volatility changes, reflecting a relatively stable market outlook.

EGARCH Daily Forecasts

```
> egforecast_IFBIND

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

0-roll forecast [T0=2024-09-27]:
        Series   Sigma
T+1  0.0014173 0.02403
T+2  0.0003822 0.02450
T+3  0.0012809 0.02495
T+4  0.0005007 0.02538
T+5  0.0011780 0.02579
T+6  0.0005899 0.02618
T+7  0.0011005 0.02655
T+8  0.0006572 0.02691
T+9  0.0010421 0.02725
T+10 0.0007079 0.02757
```

The eGARCH daily forecast for IFBIND indicates small and fluctuating positive returns over the next 10 days, starting at 0.0014173 and gradually decreasing to 0.0007079. The forecasted volatility (sigma) remains relatively stable, starting at 0.02403 and ending at 0.02757, with a slight upward trend. This forecast reflects a stable market environment with minimal changes in returns and volatility, consistent with a low-risk outlook.

Weekly Returns

CAPM Model :

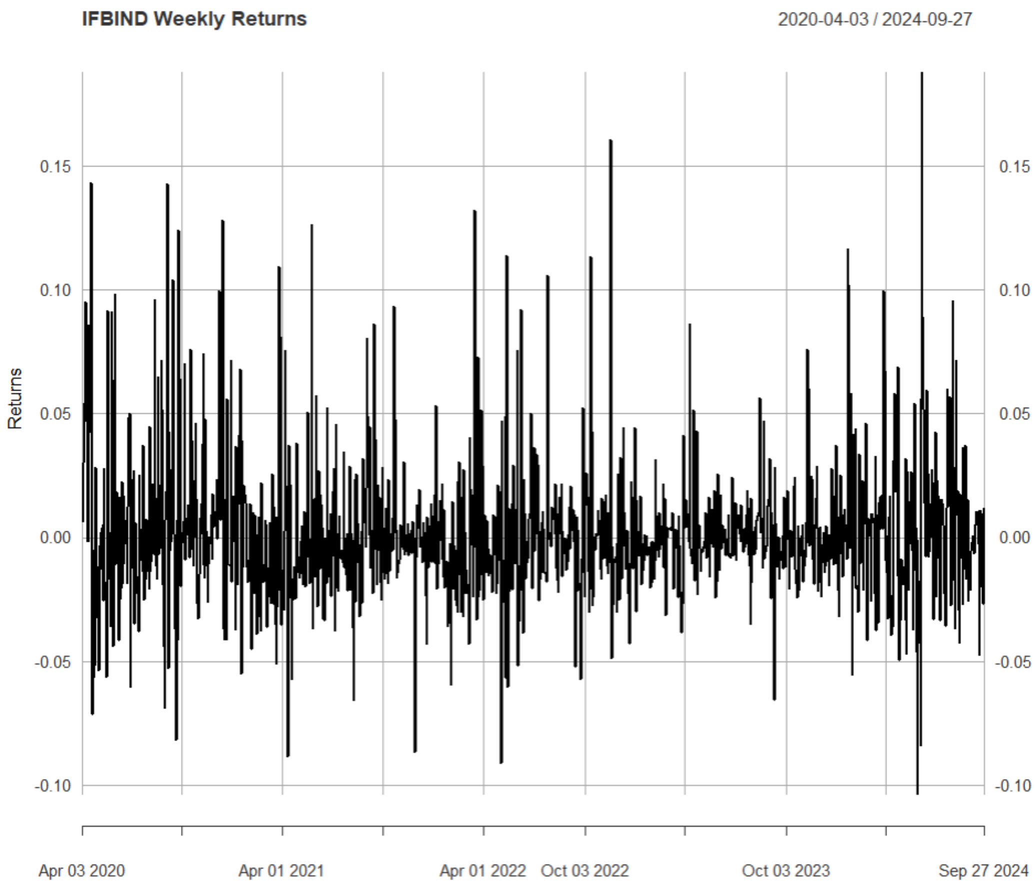
```
Call:
lm(formula = IFBIND.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
      Min        1Q    Median        3Q       Max 
-0.115591 -0.034679 -0.004287  0.024552  0.259868 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)        0.003218   0.004136   0.778    0.437    
NSEI.ExcessReturns 0.804818   0.163254   4.930 1.69e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05645 on 206 degrees of freedom
Multiple R-squared:  0.1055,	Adjusted R-squared:  0.1012 
F-statistic:  24.3 on 1 and 206 DF,  p-value: 1.69e-06
```

Weekly Returns (Beta = 0.804)

Interpretation:

The weekly beta of 0.804 shows a slight increase in responsiveness compared to daily returns but remains below 1. This means IFBIND continues to exhibit defensive characteristics while responding slightly more to market trends over a weekly horizon.

Estimating AR and MA coefficient using ARIMA model:

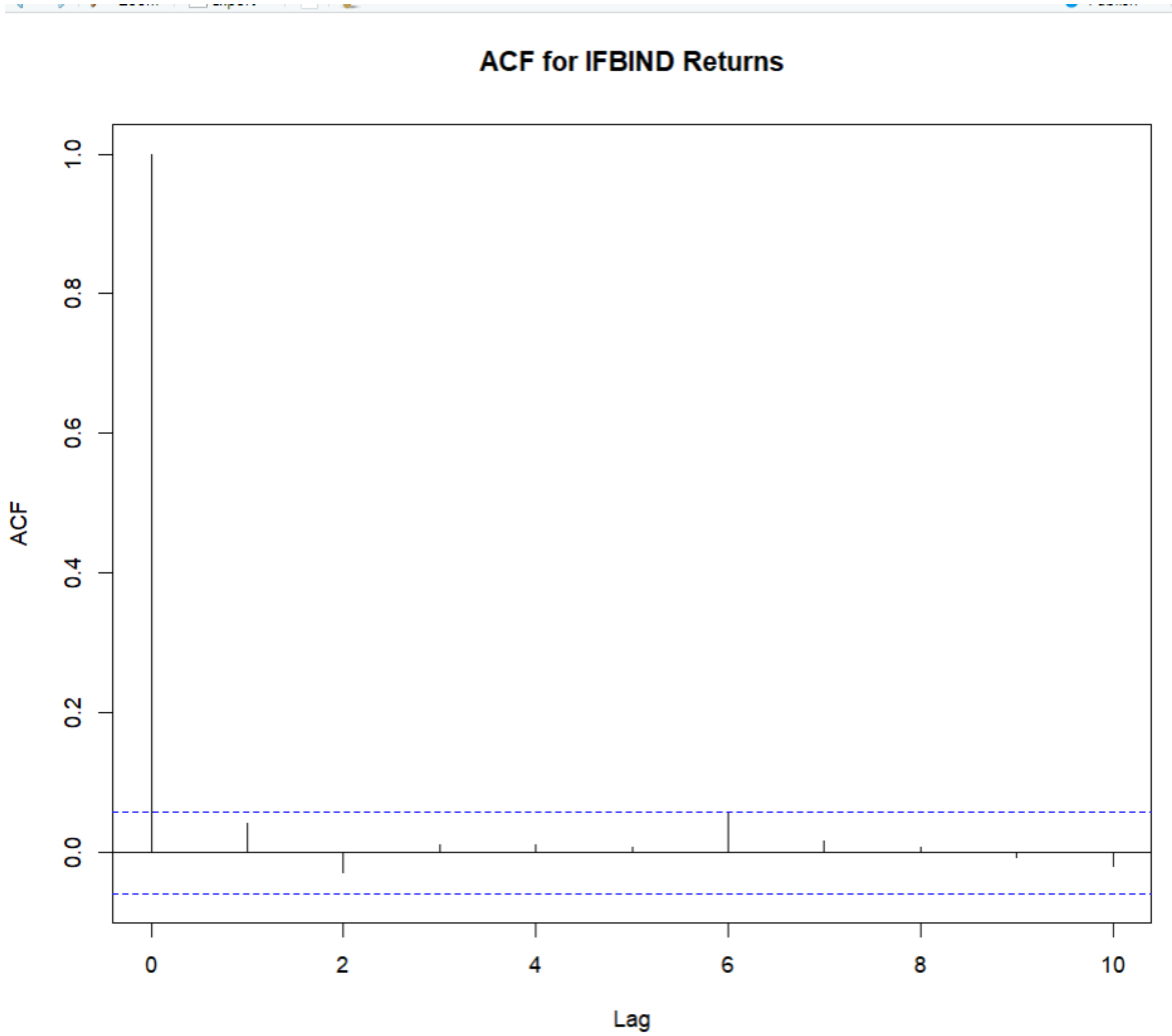


The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01 which is less than 0.05 or 5%. The experiments yielded the following results:

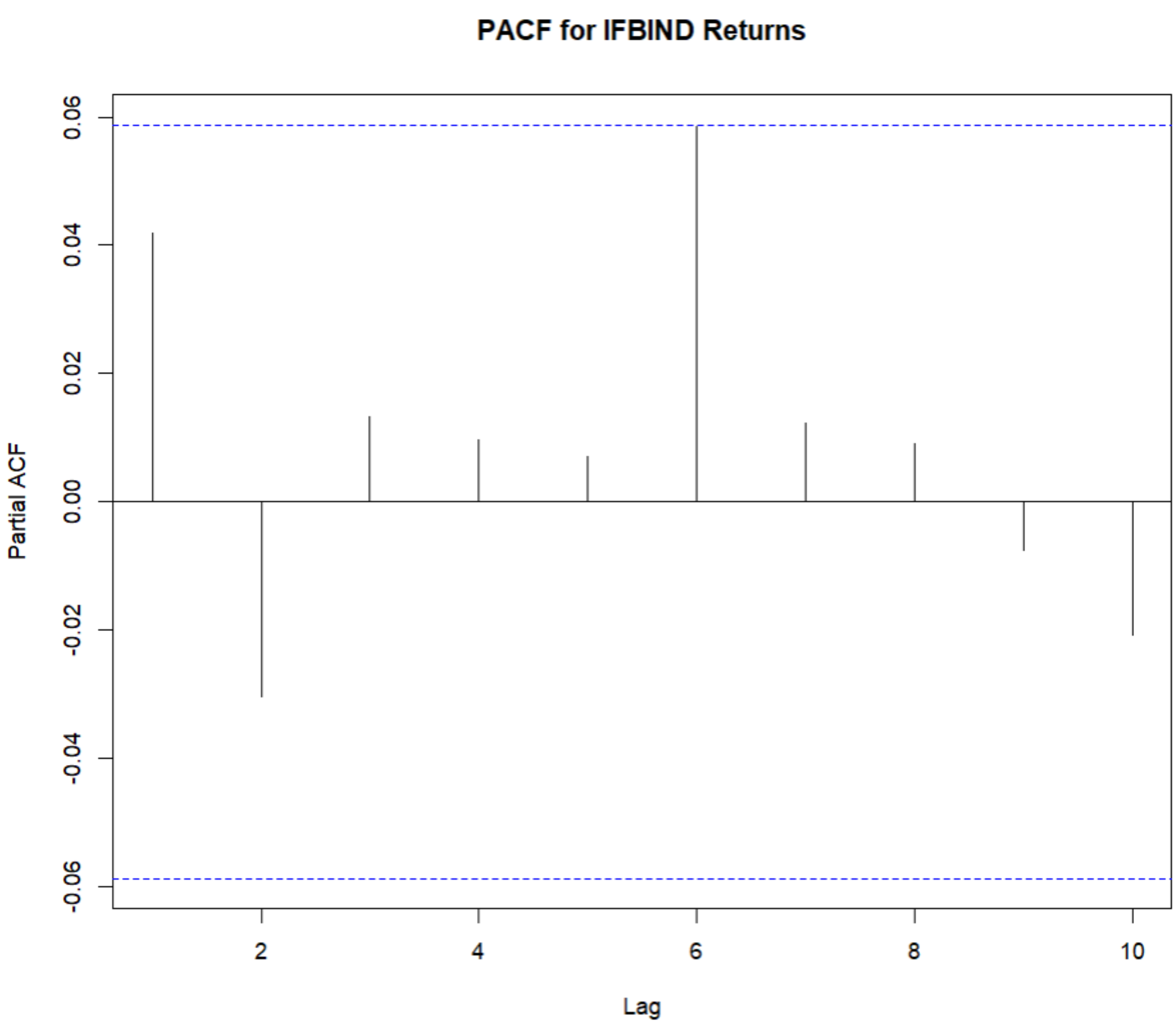
```
> adf.test(returns_IFBIND, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  returns_IFBIND
Dickey-Fuller = -10.922, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The autocorrelation function (ACF), a statistical tool, is used to determine the degree of correlation between the values in a time series. The correlation coefficient is shown against the lag, which is expressed in terms of a number of units or periods, using the ACF. The moving average model has order 1. MA (0) model is estimated.

PACF Plot:



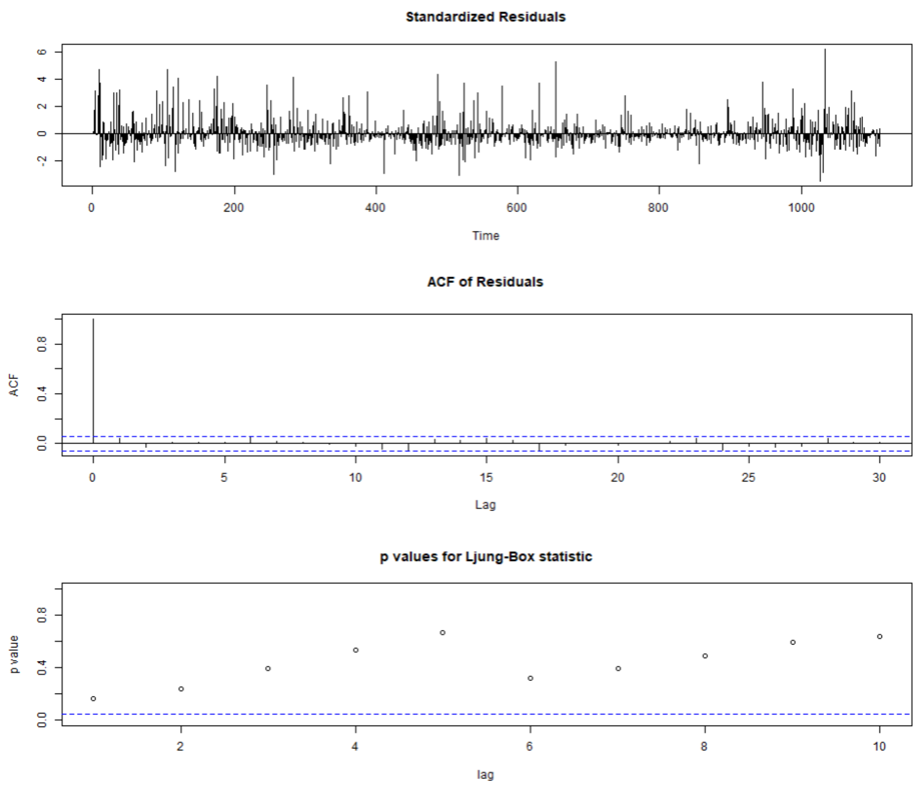
The partial autocorrelation function, or PACF, is what accounts for the partial correlation between the lags and the series.The significant partial autocorrelation at lag 1 indicates that an autoregressive (AR) model of order 1 AR(1) might be appropriate. The rapid drop in significance after lag 1 suggests that higher-order AR terms are not needed.

Following this, the ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IFBIND)

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

Coefficients:
      intercept
         0.0022
s.e.     0.0009

sigma^2 estimated as 0.0008898:  log likelihood = 2325.7,  aic = -4647.4
```

After running various (p,d,q) models we see that the least value of AIC is (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are

often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IFBIND
     Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
1112    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1113    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1114    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1115    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1116    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1117    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1118    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1119    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1120    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1121    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
```

-GARCHE & EGARCHE

-Weekly Garche

```
> 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
```

From the above analysis, we can say that GARCH(1,1) will be the most appropriate model to be used in this case and therefore we will be taking the corresponding mean model ARFIMA(1,0,1).

-Weekly EGarche

Running the EGARCH models on the weekly returns. Below are the results for the same.

```
> 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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

-Garche Model Fitting

```
> ugfit_IFBIND

*---------------------------------*
*          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      0.009801    0.007108   1.3789 0.167927
ar1     0.963133    0.063252  15.2269 0.000000
ma1    -0.941320    0.074471 -12.6400 0.000000
omega   0.000108    0.000074   1.4620 0.143728
alpha1  0.028704    0.016792   1.7094 0.087382
beta1   0.940656    0.027778  33.8639 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.009801    0.010795  0.90786  0.36395
ar1     0.963133    0.074705 12.89249  0.00000
ma1    -0.941320    0.071630 -13.14134 0.00000
omega   0.000108    0.000092  1.17372  0.24051
alpha1  0.028704    0.022665  1.26642  0.20536
beta1   0.940656    0.027390 34.34268  0.00000
```

```
LogLikelihood : 325.2308

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

Akaike       -2.7053
Bayes        -2.6173
Shibata      -2.7066
Hannan-Quinn -2.6698

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      0.458  0.4985
Lag[2*(p+q)+(p+q)-1][5]     1.090  1.0000
Lag[4*(p+q)+(p+q)-1][9]     2.728  0.9275
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.9206  0.3373
Lag[2*(p+q)+(p+q)-1][5]    2.0342  0.6104
Lag[4*(p+q)+(p+q)-1][9]    2.8937  0.7764
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.9877 0.500 2.000  0.3203
ARCH Lag[5]    1.1473 1.440 1.667  0.6898
ARCH Lag[7]    1.5814 2.315 1.543  0.8049

Nyblom stability test
```

```
------------------------------------
Joint Statistic:  1.0197
Individual Statistics:
mu     0.2020
ar1    0.1610
ma1    0.2031
omega  0.1413
alpha1 0.1218
beta1  0.1288

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            3.354 0.0009312 ***
Negative Sign Bias   2.005 0.0461519  **
Positive Sign Bias   1.478 0.1407574
Joint Effect        11.250 0.0104501  **


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     41.97    0.0017912
2    30     49.00    0.0115483
3    40     74.17    0.0005786
4    50     70.36    0.0243852


Elapsed time : 0.09833813
```

- The GARCH(1,1) model for IFBIND's weekly returns demonstrates strong performance in capturing the volatility dynamics of the series.
- The mean parameter mu (0.009801) is positive but not statistically significant (p = 0.167927), indicating minimal evidence of consistent positive returns. However, the autoregressive (ar1) parameter (0.96333) and moving average (ma1) parameter (-0.941320) are highly significant (p < 0.01), showing strong dependence on past returns and errors, respectively.
- In the variance dynamics, the omega parameter (0.000108) is positive but not significant, indicating limited baseline variance, while the ARCH effect (alpha1 = 0.028704) is marginally significant (p = 0.087382), suggesting minimal influence of recent shocks.

- The Ljung-Box tests for both standardized and squared residuals indicate no serial correlation ($p > 0.05$), confirming the model adequately captures the dependency structures in the returns.

In summary, the GARCH(1,1) model effectively captures the persistent volatility patterns in IFBIND's weekly returns and the dependence on past shocks and returns.

EGarche Model Fitting

```
> egfit_IFBIND

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.007514    0.000001   6185.7        0
ar1     0.974533    0.000107   9084.4        0
ma1    -0.972291    0.000109  -8956.8        0
omega  -0.298247    0.000034  -8706.9        0
alpha1  0.132457    0.000020   6777.9        0
beta1   0.949977    0.000097   9831.4        0
gamma1 -0.196873    0.000032  -6105.8        0

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.007514    0.000032   235.94        0
ar1     0.974533    0.000189  5167.06        0
ma1    -0.972291    0.000098 -9926.65        0
```

```
ma1    -0.972291    0.000098 -9926.65        0
omega  -0.298247    0.000413  -722.72        0
alpha1  0.132457    0.000315   420.31        0
beta1   0.949977    0.003812   249.22        0
gamma1 -0.196873    0.000848  -232.22        0

LogLikelihood : 336.1446

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

Akaike       -2.7894
Bayes        -2.6866
Shibata      -2.7911
Hannan-Quinn -2.7479

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.523  0.2172
Lag[2*(p+q)+(p+q)-1][5]     2.248  0.8914
Lag[4*(p+q)+(p+q)-1][9]     3.574  0.7862
d.o.f=2
H0 : No serial correlation

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

```
                              statistic p-value
Lag[1]                           0.1962  0.6578
Lag[2*(p+q)+(p+q)-1][5]          0.5814  0.9444
Lag[4*(p+q)+(p+q)-1][9]          1.2340  0.9744
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.3790 0.500 2.000  0.5381
ARCH Lag[5]    0.5336 1.440 1.667  0.8736
ARCH Lag[7]    1.1108 2.315 1.543  0.8949

Nyblom stability test
------------------------------------
Joint Statistic:  3.9136
Individual Statistics:
mu     0.03827
ar1    0.03811
ma1    0.03810
omega  0.03815
alpha1 0.03823
beta1  2.47015
gamma1 0.03874

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            3.403 0.0007867 ***
Negative Sign Bias   2.016 0.0450038  **
Positive Sign Bias   1.022 0.3079506    
Joint Effect        11.963 0.0075108 ***


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     37.22     0.007446
2    30     54.85     0.002581
3    40     56.20     0.036621
4    50     72.90     0.014982


Elapsed time : 0.2676039
```

- The eGARCH(1,1) model for IFBIND demonstrates robust performance in capturing the volatility dynamics of the returns. The mean model's mu (0.007514) is highly significant ($p < 0.01$), indicating a consistent baseline return.
- Diagnostics validate the model's adequacy, with a log-likelihood of 336.1446 and low Akaike Information Criterion (-2.7894), indicating a well-fitting model.
- The Ljung-Box tests for standardized and squared residuals show no serial correlation ($p > 0.05$), confirming that the model adequately captures dependency structures.
- The Sign Bias Test reveals significant bias in the negative sign ($p = 0.045$) and overall joint effect ($p = 0.007$), highlighting asymmetry in volatility responses.

Overall, the eGARCH(1,1) model captures the persistent and asymmetric volatility patterns in IFBIND's returns effectively, consistent with financial market behavior.

-GARCHE FORECASTING

```
> ugforecast_IFBIND

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

0-roll forecast [T0=2024-09-29]:
       Series   Sigma
T+1  0.009906 0.06648
T+2  0.009902 0.06627
T+3  0.009898 0.06607
T+4  0.009894 0.06587
T+5  0.009891 0.06568
T+6  0.009888 0.06550
T+7  0.009884 0.06532
T+8  0.009881 0.06514
T+9  0.009878 0.06497
T+10 0.009876 0.06481
```

The weekly forecast for IFBIND using the sGARCH model predicts stable positive returns over the next 10 weeks, with a mean return around 0.0099. The associated volatility (sigma) gradually decreases, starting from 0.06648 in week 1 to 0.06481 by week 10. This indicates a slight reduction in uncertainty over time, suggesting that the market might stabilize further in the near future. These forecasts reflect consistent returns with marginally declining risk levels.

-EGARCHE FORECASTING

```
> egforecast_IFBIND

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

0-roll forecast [T0=2024-09-29]:
        Series   Sigma
T+1   0.007796 0.06125
T+2   0.007789 0.06068
T+3   0.007782 0.06013
T+4   0.007775 0.05963
T+5   0.007768 0.05915
T+6   0.007762 0.05869
T+7   0.007755 0.05827
T+8   0.007749 0.05787
T+9   0.007743 0.05749
T+10  0.007738 0.05713
```

The weekly forecast for IFBIND using the eGARCH model predicts slightly lower positive returns, stabilizing around 0.0077 over the next 10 weeks. The forecasted volatility (sigma) gradually decreases from 0.06125 in week 1 to 0.05713 by week 10. This indicates a consistent reduction in risk, suggesting a stable market environment with less uncertainty, while maintaining steady positive returns.

Monthly Returns

CAPM

```
Call:
lm(formula = exStock ~ exNSE, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.23144 -0.08841 -0.02843  0.06830  0.43964

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.03798    0.05859   0.648     0.52
exNSE        1.04691    0.13470   7.772 2.59e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.145 on 53 degrees of freedom
Multiple R-squared:  0.5327,    Adjusted R-squared:  0.5238
F-statistic: 60.41 on 1 and 53 DF,  p-value: 2.588e-10
```

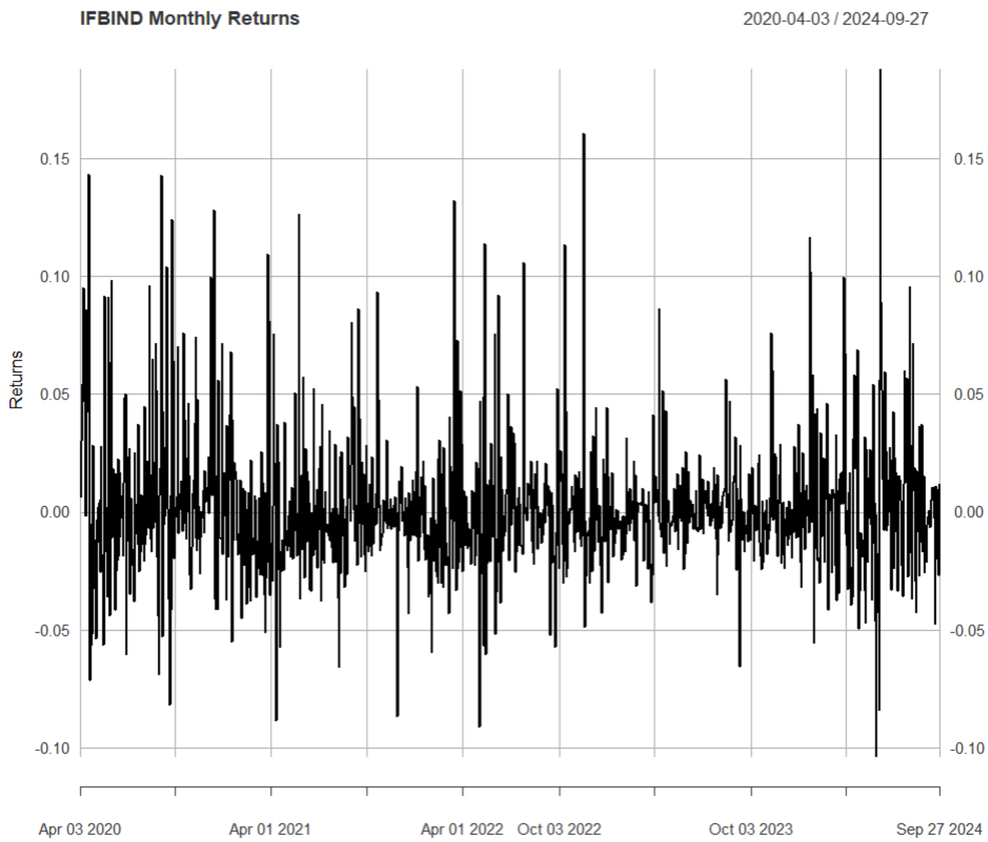
Monthly Returns (Beta = 1.046)

Interpretation:

On a monthly scale, it is found that IFBIND gets more close to the market with a beta of 1.046. This means the stock remains stable in the short term but would be equal to the movement that takes place within the market when tracked in the long term.

Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

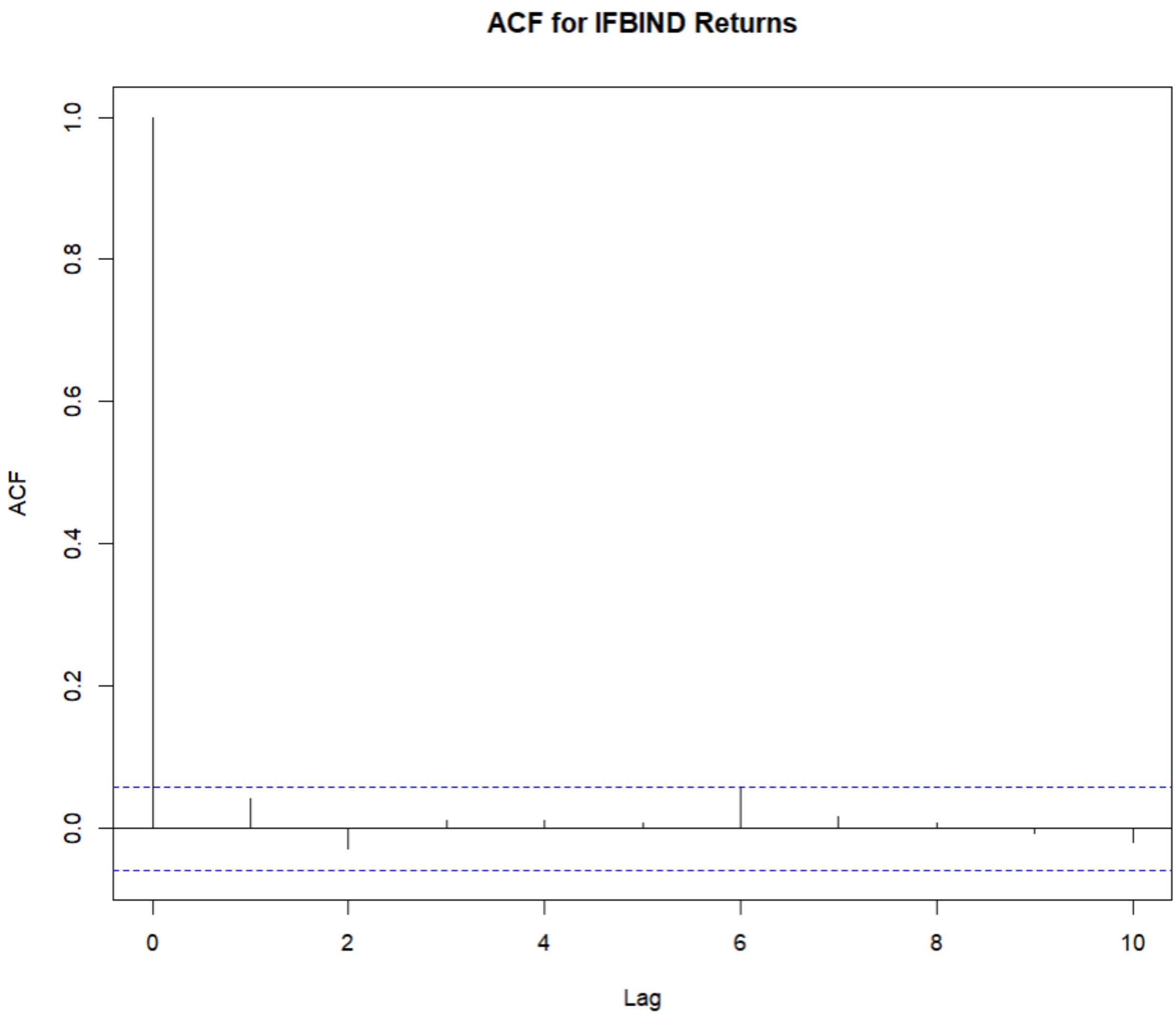


The variance of returns is constant for the analysis period. An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p – value from the Augmented Dickey-Fuller Test is less than 0.05 which shows that the series is stationary.

The experiments yielded the following results:

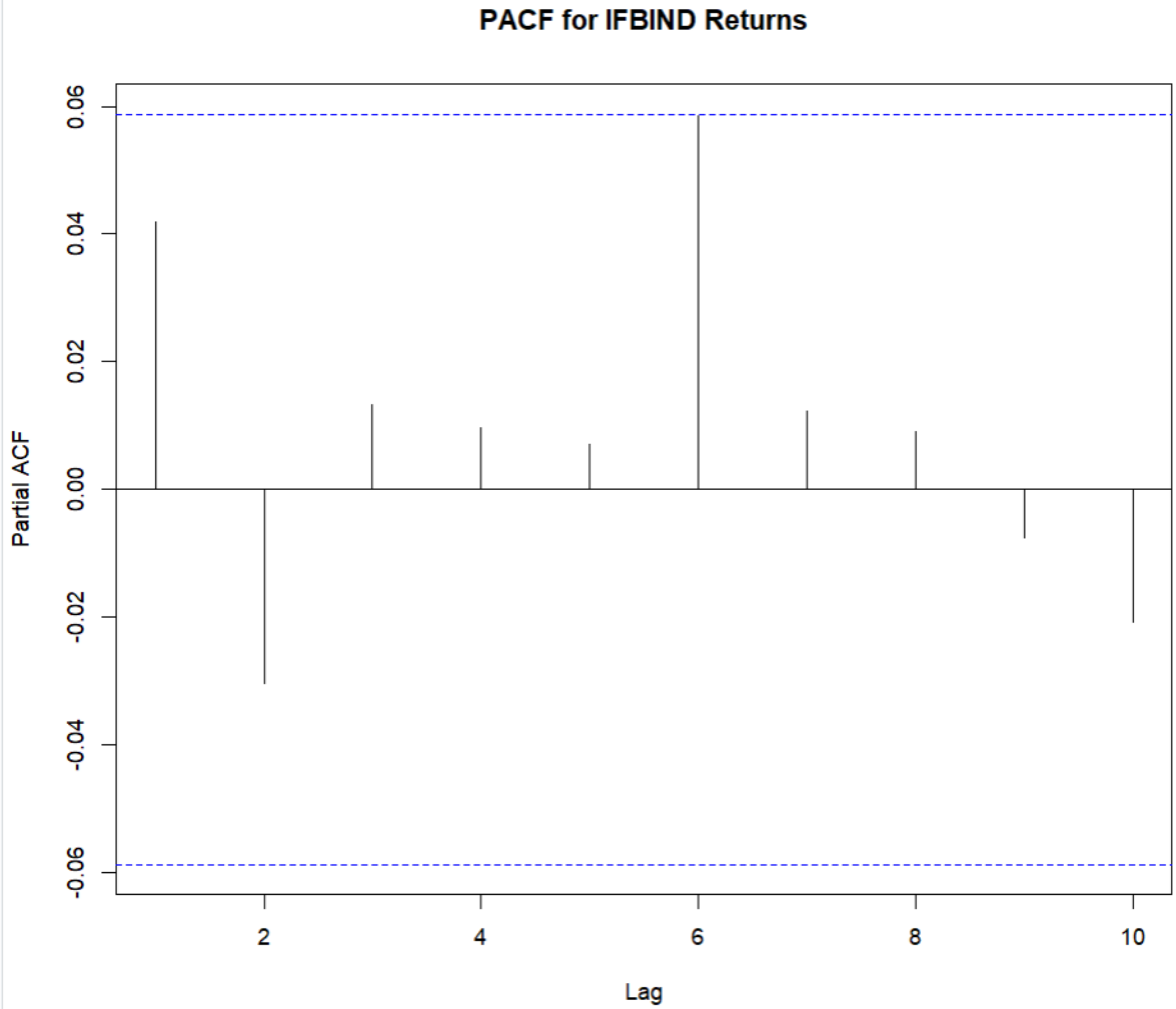
```
> adf.test(returns_IFBIND, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  returns_IFBIND
Dickey-Fuller = -10.922, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot:



From the plot, there is a significant spike at lag 1, indicating that the first lag is likely an important predictor in the model. The lags (i.e. at 3, 6, 8) do not exceed the confidence bands by a large margin and may be considered non-significant. Based on the significant partial autocorrelation at lag 1 and the drop-off afterward, an AR(1) model is proposed for the given plot.

Following this, the ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IFBIND)

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

Coefficients:
      intercept
         0.0022
s.e.     0.0009

sigma^2 estimated as 0.0008898:  log likelihood = 2325.7,  aic = -4647.4

Training set error measures:
                        ME       RMSE        MAE  MPE MAPE      MASE      ACF1
Training set -3.758966e-18 0.02982889 0.01993537 -Inf  Inf 0.6996171 0.0418626
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IFBIND
     Point Forecast       Lo 80      Hi 80       Lo 95      Hi 95
1112    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1113    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1114    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1115    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1116    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1117    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1118    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1119    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1120    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
1121    0.002155823 -0.03607144 0.04038308 -0.05630773 0.06061937
```

-**Garche & EGarche**

-Garche Model Fitting

```
> ugfit_IFBIND

*---------------------------------*
*          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      0.043364    0.020486  2.11673 0.034282
ar1    -0.523610    0.577226 -0.90712 0.364346
ma1     0.435811    0.601135  0.72498 0.468464
omega   0.001226    0.001212  1.01163 0.311715
alpha1  0.000000    0.031774  0.00000 1.000000
beta1   0.935457    0.110413  8.47232 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.043364    0.027082  1.60123 0.109326
ar1    -0.523610    0.277685 -1.88563 0.059345
ma1     0.435811    0.332630  1.31020 0.190129
omega   0.001226    0.002185  0.56099 0.574806
alpha1  0.000000    0.023203  0.00000 1.000000
beta1   0.935457    0.120391  7.77014 0.000000

LogLikelihood : 21.69647

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

Akaike       -0.58135
Bayes        -0.36035
Shibata      -0.60290
```

```
Hannan-Quinn -0.49612

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.02614  0.8715
Lag[2*(p+q)+(p+q)-1][5]   0.54802  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.71029  0.9936
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.02262  0.8804
Lag[2*(p+q)+(p+q)-1][5]   1.20260  0.8124
Lag[4*(p+q)+(p+q)-1][9]   3.59817  0.6575
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.04495 0.500 2.000  0.8321
ARCH Lag[5]   1.49857 1.440 1.667  0.5927
ARCH Lag[7]   2.17595 2.315 1.543  0.6801

Nyblom stability test
------------------------------------
Joint Statistic:  1.0501
Individual Statistics:
mu     0.2468
ar1    0.2884
ma1    0.3503
omega  0.1324
```

```
alpha1 0.1246
beta1  0.1325

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           0.7063 0.4833
Negative Sign Bias  1.1037 0.2751
Positive Sign Bias  0.4330 0.6669
Joint Effect        1.5417 0.6727


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     26.74      0.11084
2    30     36.00      0.17356
3    40     61.56      0.01211
4    50     57.11      0.19917


Elapsed time : 0.069103
```

The GARCH(1,1) model for IFBIND's monthly returns shows a moderate fit with a log-likelihood of 21.69647, and the model's information criteria (Akaike: -0.58135, Bayes: -0.36035) indicate acceptable model adequacy. The mean parameter mu is 0.043364, with marginal significance (p = 0.034282), suggesting a baseline positive return, while the autoregressive (ar1) and moving average (ma1) terms are not significant, indicating limited reliance on past values or errors in return prediction. The volatility parameters reveal notable insights; beta1 (0.935457) is highly significant (p < 0.01), indicating strong persistence of volatility over time, while alpha1 is effectively zero, suggesting minimal impact of immediate past shocks on current volatility. The diagnostic tests show no serial correlation in standardized or squared residuals, as confirmed by the Ljung-Box and ARCH LM tests with p-values exceeding 0.05, validating the model's ability to capture the dependency structure. The Nyblom stability test returns a joint statistic of 1.0501, below the critical threshold of 1.49 at the 10% level, indicating stable model parameters over time. The Sign Bias Test finds no evidence of asymmetric volatility responses, as all p-values are greater than 0.05, implying balanced reactions to positive and negative shocks. The Adjusted Pearson Goodness-of-Fit Test suggests that the model fits well for most group sizes, though a notable exception occurs for group sizes of 40 data points, where the p-value is 0.01211.

Overall, the GARCH(1,1) model effectively captures the persistence of volatility in IFBIND's monthly returns, though its reliance on immediate past shocks appears limited. The absence of serial correlation and parameter instability reinforces the model's validity, but the marginal significance of the mean return and certain limitations in group fit suggest room for improvement or further refinement in forecasting monthly returns

-EGarche Model Fitting

```
> egfit_IFBIND

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

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

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.047388    0.000016   3015.7        0
ar1    -0.583311    0.000137  -4257.2        0
ma1     0.360899    0.000086   4204.1        0
omega  -0.437210    0.000116  -3765.9        0
alpha1  0.352415    0.000078   4520.6        0
beta1   0.884941    0.000207   4284.2        0
gamma1 -0.831101    0.000165  -5027.1        0


alpha1  0.352415    0.005641   62.471        0
beta1   0.884941    0.041169   21.495        0
gamma1 -0.831101    0.009001  -92.332        0

LogLikelihood : 27.15974

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

Akaike       -0.74666
Bayes        -0.48883
Shibata      -0.77539
Hannan-Quinn -0.64722

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.6088  0.4353
Lag[2*(p+q)+(p+q)-1][5]    1.4437  0.9987
Lag[4*(p+q)+(p+q)-1][9]    3.0786  0.8784
d.o.f=2
H0 : No serial correlation

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

```
Lag[1]                        0.2006  0.6542
Lag[2*(p+q)+(p+q)-1][5]       1.5937  0.7168
Lag[4*(p+q)+(p+q)-1][9]       2.9124  0.7733
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     0.381 0.500 2.000  0.5371
ARCH Lag[5]     1.479 1.440 1.667  0.5979
ARCH Lag[7]     1.985 2.315 1.543  0.7206

Nyblom stability test
------------------------------------
Joint Statistic:  7.1531
Individual Statistics:
mu     0.02930
ar1    0.03369
ma1    0.02916
omega  0.03829
alpha1 0.02919
beta1  0.13969
gamma1 0.02917

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          0.15524 0.8773
Negative Sign Bias 1.01694 0.3142
Positive Sign Bias 0.08319 0.9340
Joint Effect       2.44291 0.4857


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     44.52    0.0008001
2    30     41.56    0.0615336
3    40     60.07    0.0166588
4    50     66.37    0.0497302


Elapsed time : 0.1814661
```

The eGARCH(1,1) model for IFBIND’s monthly returns demonstrates a strong ability to capture volatility dynamics, as reflected by a log-likelihood of 27.15974 and low values for the information criteria (Akaike: -0.74666, Bayes: -0.48883). The mean parameter mu (0.047388) is highly significant ($p < 0.01$), indicating consistent positive returns. The autoregressive (ar1) and moving average (ma1) terms are also highly significant, with estimates of -0.583311 and 0.360899, respectively, suggesting that both past returns and past errors play a crucial role in influencing current returns. The variance dynamics reveal notable patterns. The parameter omega (-0.437210) is negative and significant, consistent with leverage effects where negative shocks lead to higher volatility. The ARCH effect (alpha1 = 0.352415) and GARCH effect (beta1 = 0.884941) are significant, indicating that both past shocks and volatility persistence heavily influence current volatility. The asymmetry parameter gamma1 (-0.831101) is significant and negative, highlighting the model's ability to capture asymmetric volatility where negative returns have a larger impact on volatility than positive ones.

Diagnostic tests validate the model's robustness. The Ljung-Box test for standardized and squared residuals shows no serial correlation ($p > 0.05$), confirming that the model adequately captures return dependencies. The ARCH LM test indicates no remaining ARCH effects, with all p-values exceeding 0.05. However, the Nyblom stability test reveals parameter instability, with a joint statistic of 7.1531 exceeding the critical thresholds, suggesting that some parameters may vary over time. The Sign Bias Test indicates no significant sign bias ($p > 0.05$), suggesting balanced responses to positive and negative shocks. The Adjusted Pearson Goodness-of-Fit test shows good overall fit, though group sizes of 20 and 40 exhibit some deviation (p-values of 0.0008 and 0.0166, respectively).

In summary, the eGARCH(1,1) model effectively captures the volatility structure of IFBIND's monthly returns, including persistence and asymmetry in volatility responses. While diagnostic tests validate the model's adequacy, parameter instability and slight goodness-of-fit deviations in specific group sizes suggest areas for further refinement.

-Garche Forecasting

```
> ugforecast_IFBIND

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

0-roll forecast [T0=2024-08-31]:
      Series  Sigma
T+1  0.05943 0.1386
T+2  0.03495 0.1386
T+3  0.04777 0.1385
T+4  0.04106 0.1385
T+5  0.04457 0.1384
T+6  0.04273 0.1384
T+7  0.04369 0.1383
T+8  0.04319 0.1383
T+9  0.04345 0.1383
T+10 0.04332 0.1382
```

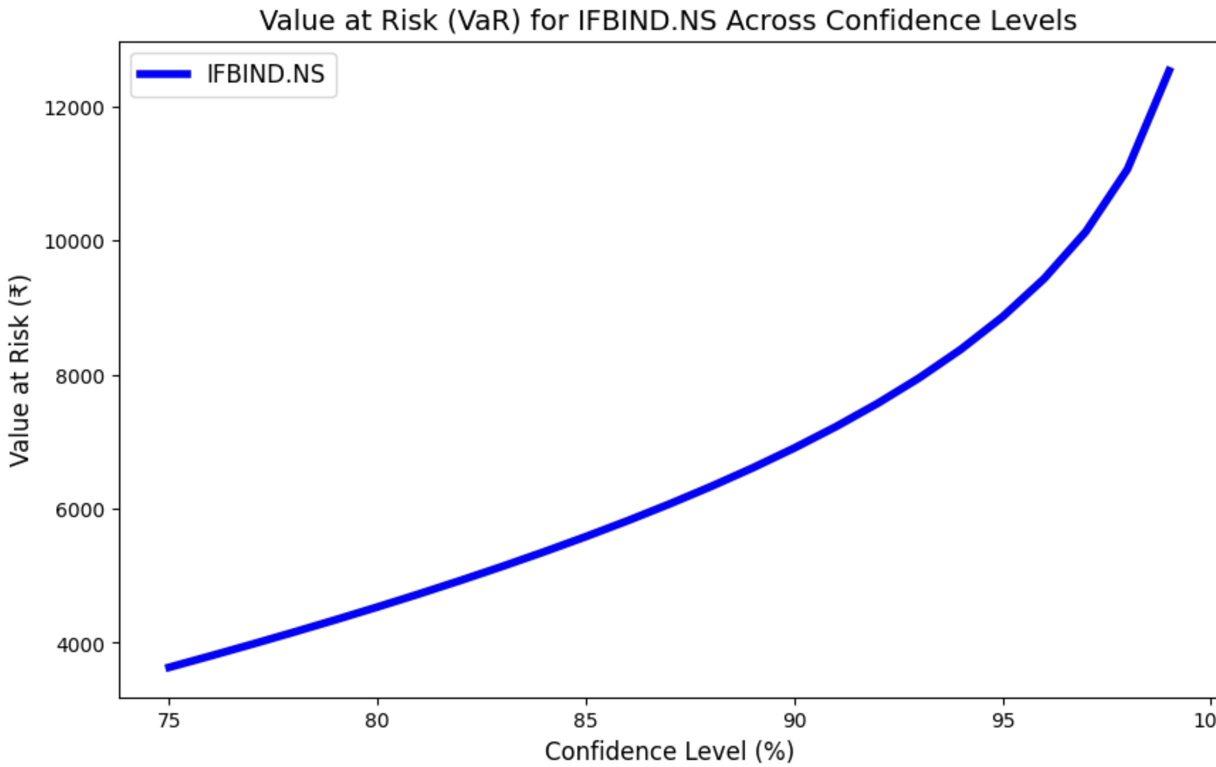
The monthly forecast for IFBIND using the sGARCH model predicts a gradual stabilization of returns, starting at 0.05943 in the first month and decreasing to 0.04332 by the tenth month. The volatility (sigma) remains consistently high but shows a marginal decline, reducing from 0.1386 in the first month to 0.1382 in the tenth month. This forecast reflects a steady decrease in returns while maintaining relatively constant risk levels, suggesting a cautious market environment with persistent uncertainty.

-EGarche Forecasting

```
> egforecast_IFBIND

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

0-roll forecast [T0=2024-08-31]:
      Series  Sigma
T+1  0.08459 0.1943
T+2  0.02569 0.1886
T+3  0.06004 0.1836
T+4  0.04001 0.1793
T+5  0.05169 0.1756
T+6  0.04488 0.1724
T+7  0.04885 0.1696
T+8  0.04653 0.1672
T+9  0.04789 0.1650
T+10 0.04710 0.1632
```

The monthly forecast for IFBIND using the eGARCH model predicts fluctuating returns over the next 10 months, with the highest return in the first month (0.08459) gradually stabilizing around 0.04710 by the tenth month. The volatility (sigma) starts at 0.1943 and steadily decreases to 0.1632, indicating a reduction in market uncertainty over time. This forecast suggests that while initial returns are volatile, the market is expected to stabilize, with both returns and risk converging to more consistent levels as time progresses.

Calculating Value at Risk For IFBIND:-



Value at Risk (VaR) calculates the possible decline in the value of an investment or portfolio over a given period of time, assuming a particular degree of confidence (e.g., 95% or 99%).It helps investors and institutions comprehend the worst-case scenario under typical market conditions by giving them a measurable indicator of downside risk.

Above is the graph for IFBIND, showing the value at risk at different confidence intervals from 75% to 100%. At 75% confidence level, VaR is 4,000, which means that there is only a 25% chance that the stock price will fall by 4,000 rupees in a day. Similarly, VaR at 95% confidence level is 10,000, which means that there is only a 5% chance that the stock price will fall by 10,000 rupees in a day. At 100% confidence level, there is no chance that the stock price will fall by more than 12,000 rupees.

IMFA (Indian Metals and Ferro Alloys Ltd)

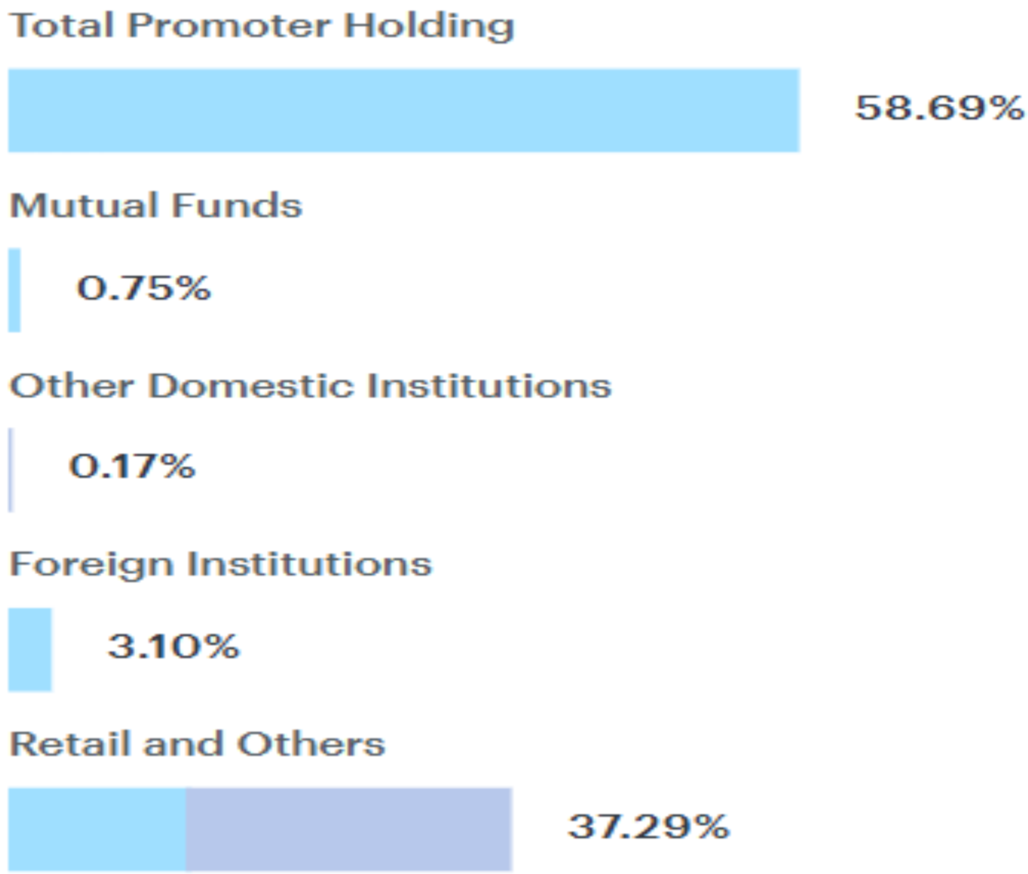
About the company

1.1.1 Nature of the business

IMFA is India's leading and fully integrated producer of ferro alloys, particularly focusing on ferro chrome. The company operates across the entire value chain from mining to smelting, with a significant presence in the global market. Its product line primarily serves the steel industry, providing essential materials for stainless steel manufacturing. IMFA is also known for its sustainability efforts, operating one of the largest captive power plants among ferro alloy producers in India.

1.1.2 Ownership category

IMFA is a publicly listed company, incorporated as Indian Metals & Ferro Alloys Limited. It trades on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) under the ticker symbols "IMFA" and "533047," respectively. The company was founded by Dr. Bansidhar Panda and has remained largely under the stewardship of the Panda family, with the current leadership comprising several family members in key executive roles.



IMFA Shareholding pattern

1.1.3 When did it start?

IMFA was established in 1961 in Odisha, leveraging the region's rich natural resources. Over the decades, it has expanded significantly, especially after establishing large manufacturing complexes in Therubali and Choudwar, Odisha. These facilities include a combination of chrome ore mines, smelting units, and captive power generation, making IMFA one of the most vertically integrated players in the ferro alloy industry.

1.1.4. Significance in the industry

IMFA is a leader in India's ferro alloys sector, particularly as the largest integrated producer of ferro chrome, with an annual capacity of 284,000 tonnes. The company's competitive edge is bolstered by its captive chrome ore mines and extensive power generation capabilities, ensuring both cost efficiency and supply stability. IMFA is certified with ISO 9001:2015, which emphasizes its commitment to quality. It has established strong international ties with companies like POSCO and Marubeni, alongside major domestic partners like Jindal Stainless.

1.1.5. Overall greatness of the company

IMFA's strength lies in its fully integrated business model, from mining to power generation and smelting. This integration allows for greater control over production costs and quality, making it a reliable supplier in global markets. The company's dedication to sustainability is reflected in innovative projects like the LDA plant that repurposes fly ash for construction materials. With a robust track record of resilience and growth, IMFA continues to enhance its market position while embracing sustainable practices.

DAILY RETURNS

CAPM

```
Call:
lm(formula = IMFA.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
     Min       1Q   Median       3Q      Max
-0.09264 -0.01689 -0.00401  0.01396  0.12251

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.002008   0.001309   1.533    0.125
NSEI.ExcessReturns 1.012502   0.078315  12.929   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02765 on 967 degrees of freedom
Multiple R-squared:  0.1474,    Adjusted R-squared:  0.1465
F-statistic: 167.1 on 1 and 967 DF,  p-value: < 2.2e-16
```

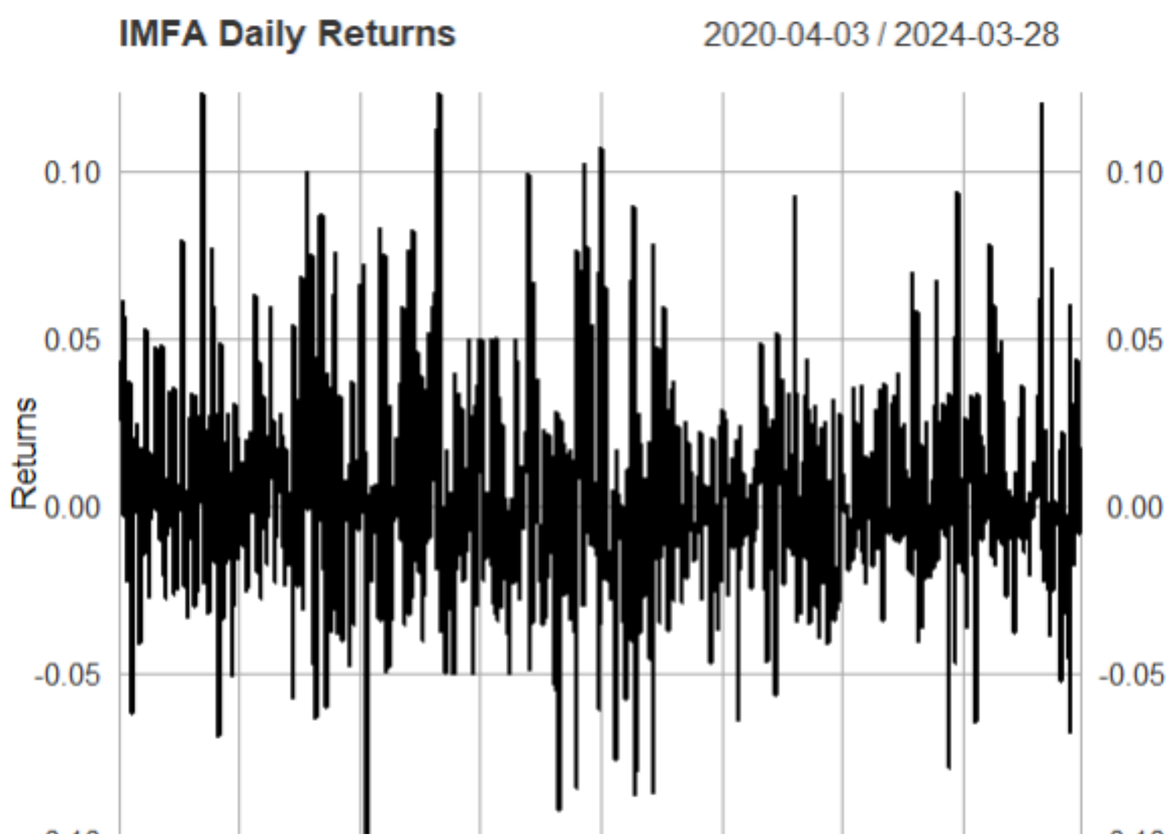
Daily Returns (Beta = 1.012)

Interpretation:

IMFA's daily beta of 1.012 reflected the stock was moderately volatile, and its returns went almost in near proportion to the market daily. This would indicate that the stock responded to the market with average sensitivity, a middle ground for short-term traders.

Estimating AR and MA coefficient using ARIMA model

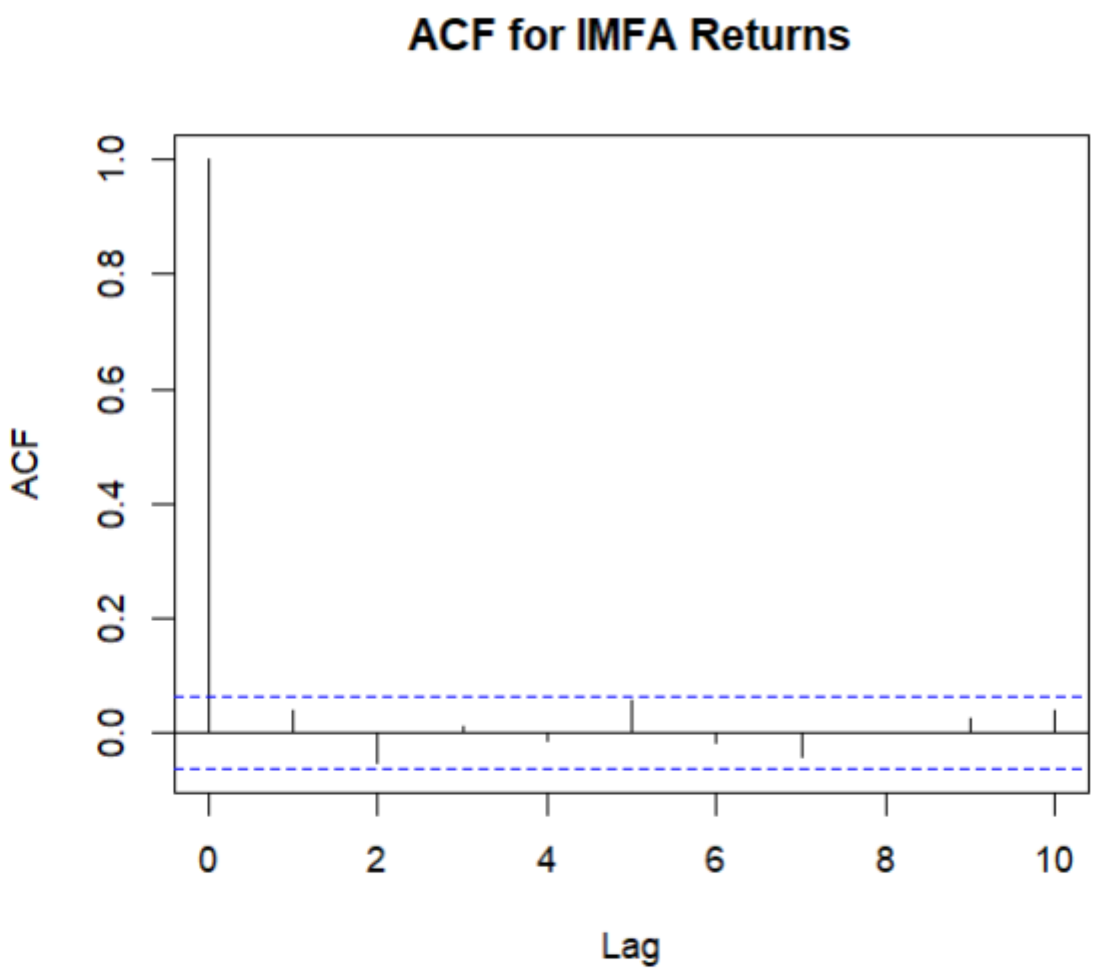
The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.



An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01, which is less than 0.05 or 5%. Hence, the series is stationary and rejects the null hypothesis. The experiments yielded the following results:

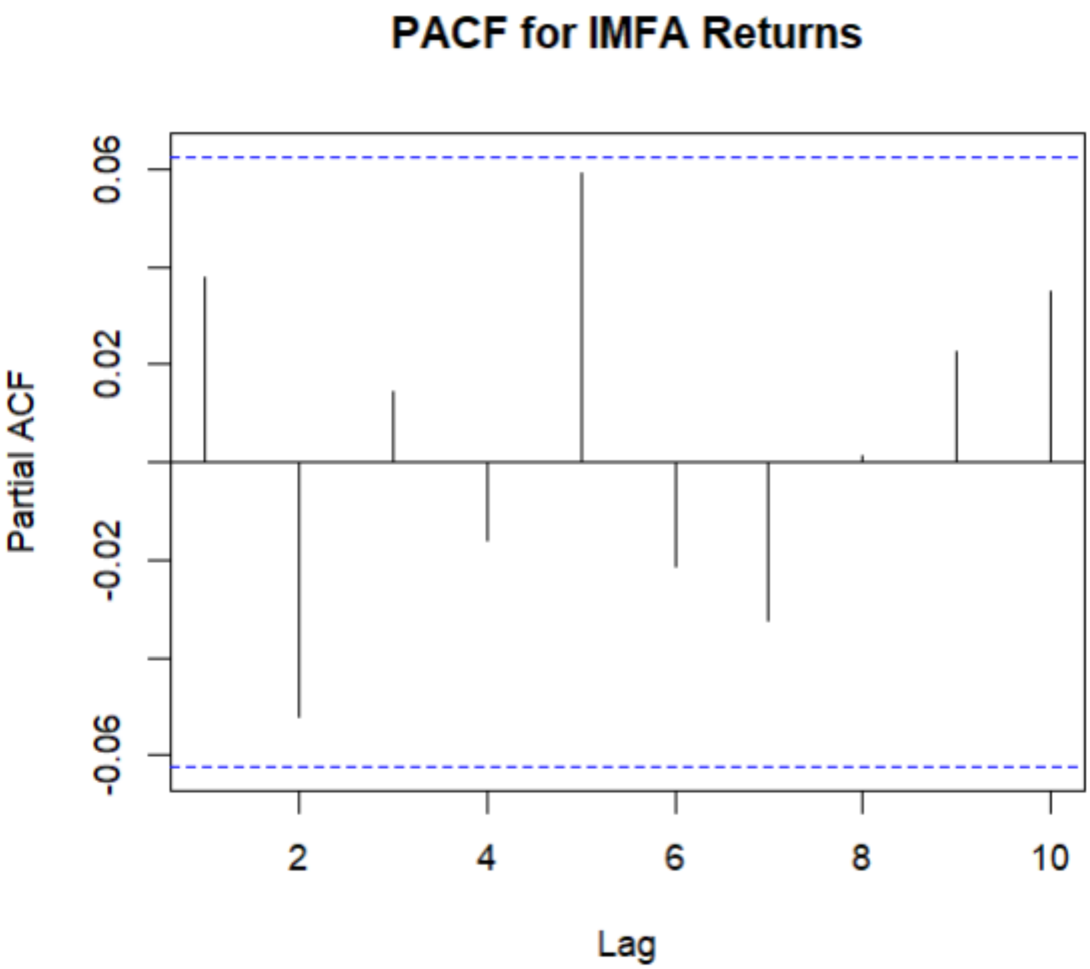
```
        Augmented Dickey-Fuller Test

data:  returns_IMFA
Dickey-Fuller = -9.4116, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF plot:



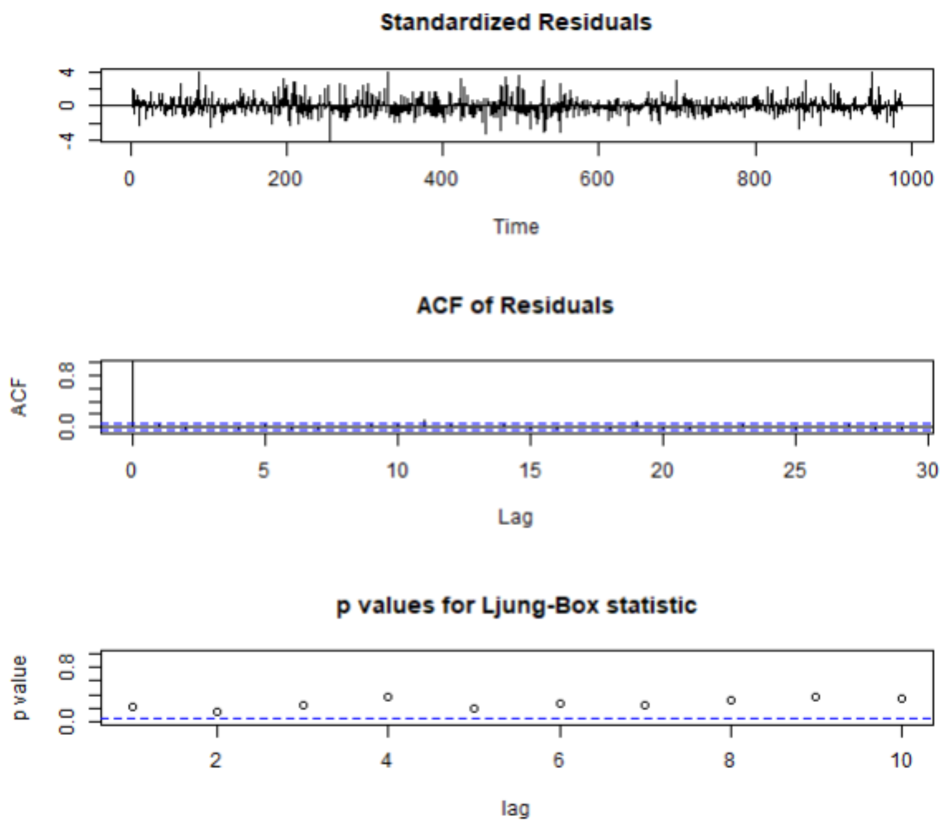
Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero.

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IMFA)

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

Coefficients:
      intercept
         0.0029
s.e.     0.0009

sigma^2 estimated as 0.0008773:  log likelihood = 2075.17,  aic = -4146.33

Training set error measures:
                       ME       RMSE        MAE  MPE MAPE      MASE       ACF1
Training set 2.094094e-15 0.02961987 0.02191848 -Inf  Inf 0.7208812 0.03789358
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are

often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model

```
> predicted_IMFA
    Point Forecast       Lo 80      Hi 80      Lo 95      Hi 95
989    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
990    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
991    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
992    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
993    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
994    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
995    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
996    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
997    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
998    0.002913483 -0.03504591 0.04087287 -0.0551404 0.06096736
```

Forecasting Volatility using GARCH and RGARCH models:

We run the GARCH models again on daily returns.

```
*---------------------------------*
*       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 : GARCH model specs for daily returns

From 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:

```
*---------------------------------*
*       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
```

Fig : EGARCH specs for daily returns

Estimating the model:

```
> ugfit_IMFA

*---------------------------------*
*          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      0.001849    0.000860   2.1502 0.031536
ar1    -0.600026    0.356930  -1.6811 0.092749
ma1     0.636355    0.342536   1.8578 0.063201
omega   0.000148    0.000045   3.3178 0.000907
alpha1  0.133073    0.031984   4.1606 0.000032
beta1   0.704889    0.068837  10.2400 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001849    0.000897   2.0618 0.039225
ar1    -0.600026    0.281244  -2.1335 0.032886
ma1     0.636355    0.268340   2.3715 0.017718
omega   0.000148    0.000068   2.1724 0.029824
alpha1  0.133073    0.047929   2.7765 0.005496
beta1   0.704889    0.106733   6.6042 0.000000
```

```
LogLikelihood : 2355.933

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

Akaike       -4.2265
Bayes        -4.1994
Shibata      -4.2266
Hannan-Quinn -4.2163

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.03265  0.8566
Lag[2*(p+q)+(p+q)-1][5]   0.19422  1.0000
Lag[4*(p+q)+(p+q)-1][9]   1.38841  0.9982
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.6147  0.4330
Lag[2*(p+q)+(p+q)-1][5]    2.8016  0.4445
Lag[4*(p+q)+(p+q)-1][9]    5.1499  0.4077
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.01194 0.500 2.000  0.9130
ARCH Lag[5]   3.94755 1.440 1.667  0.1787
ARCH Lag[7]   4.88791 2.315 1.543  0.2361
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  1.4529
Individual Statistics:
mu     0.3485
ar1    0.4630
ma1    0.4960
omega  0.2671
alpha1 0.1545
beta1  0.2965

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           1.8257 0.06817   *
Negative Sign Bias  0.4447 0.65660
Positive Sign Bias  0.5816 0.56096
Joint Effect        4.1228 0.24850


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     98.32    1.076e-12
2    30    119.94    5.032e-13
3    40    135.84    1.220e-12
4    50    137.37    2.591e-10


Elapsed time : 0.3631749
```

Fig : Diagnostic Test of GARCH Model for Daily Returns

Interpretation:

- The Log-likelihood of the model is 2355.933. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be

rejected and hence the observed values and expected values do not differ by a lot.

GARCH Model Forecast:

```
> ugforecast_IMFA

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

0-roll forecast [T0=2024-09-27]:
       Series   Sigma
T+1  0.002483 0.02355
T+2  0.001469 0.02476
T+3  0.002078 0.02573
T+4  0.001712 0.02651
T+5  0.001932 0.02715
T+6  0.001800 0.02768
T+7  0.001879 0.02811
T+8  0.001832 0.02847
T+9  0.001860 0.02876
T+10 0.001843 0.02901
```

The above table shows the forecasted value using the GARCH model for the daily return.

Forecasting using the e Garch MODEL

```
> egforecast_IMFA

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

0-roll forecast [T0=2024-09-27]:
       Series   Sigma
T+1  0.002363 0.02218
T+2  0.001764 0.02329
T+3  0.002164 0.02427
T+4  0.001897 0.02513
T+5  0.002075 0.02588
T+6  0.001956 0.02654
T+7  0.002036 0.02711
T+8  0.001983 0.02759
T+9  0.002018 0.02802
T+10 0.001994 0.02838
```

The result of forecasting is shown in Figure . The results show that the returns will be positive on average for the next 10 days, with a mean value of 0.02% and a standard deviation of 3.5%.

WEEKLY RETURNS

CAPM

```
Call:
lm(formula = IMFA.ExcessReturns ~ NSEI.ExcessReturns, data = as.data.frame(returns[]))

Residuals:
     Min       1Q   Median       3Q      Max 
-0.24476 -0.04092 -0.01116  0.02711  0.30330 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)        0.008406   0.004866   1.728   0.0855 .  
NSEI.ExcessReturns 0.887174   0.192031   4.620 6.76e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0664 on 206 degrees of freedom
Multiple R-squared:  0.09388,	Adjusted R-squared:  0.08949 
F-statistic: 21.34 on 1 and 206 DF,  p-value: 6.759e-06
```

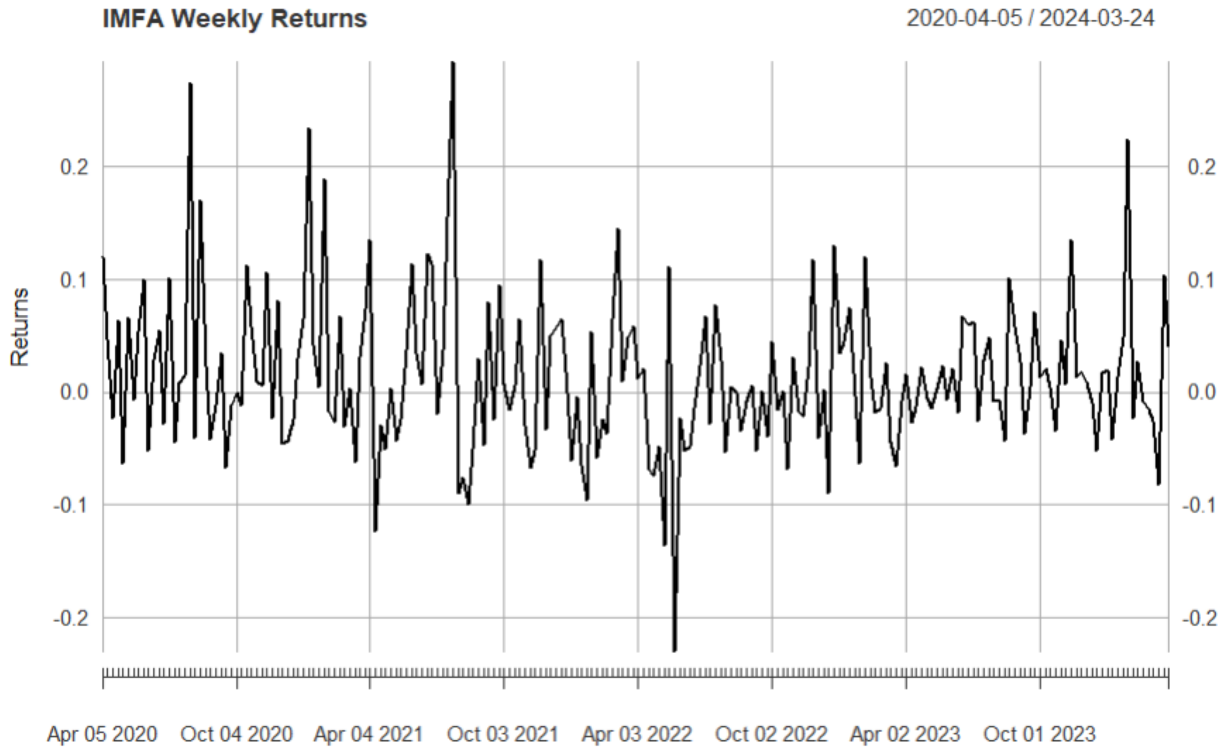
Weekly Returns (Beta = 0.887)

Interprets:

The weekly beta is 0.887, reflecting predictable responsiveness to market movement over the weekly period. This stability across timeframes makes IMFA a dependable stock for risk-averse investors desirous of predictable market action.

Estimating AR and MA coefficient using ARIMA model

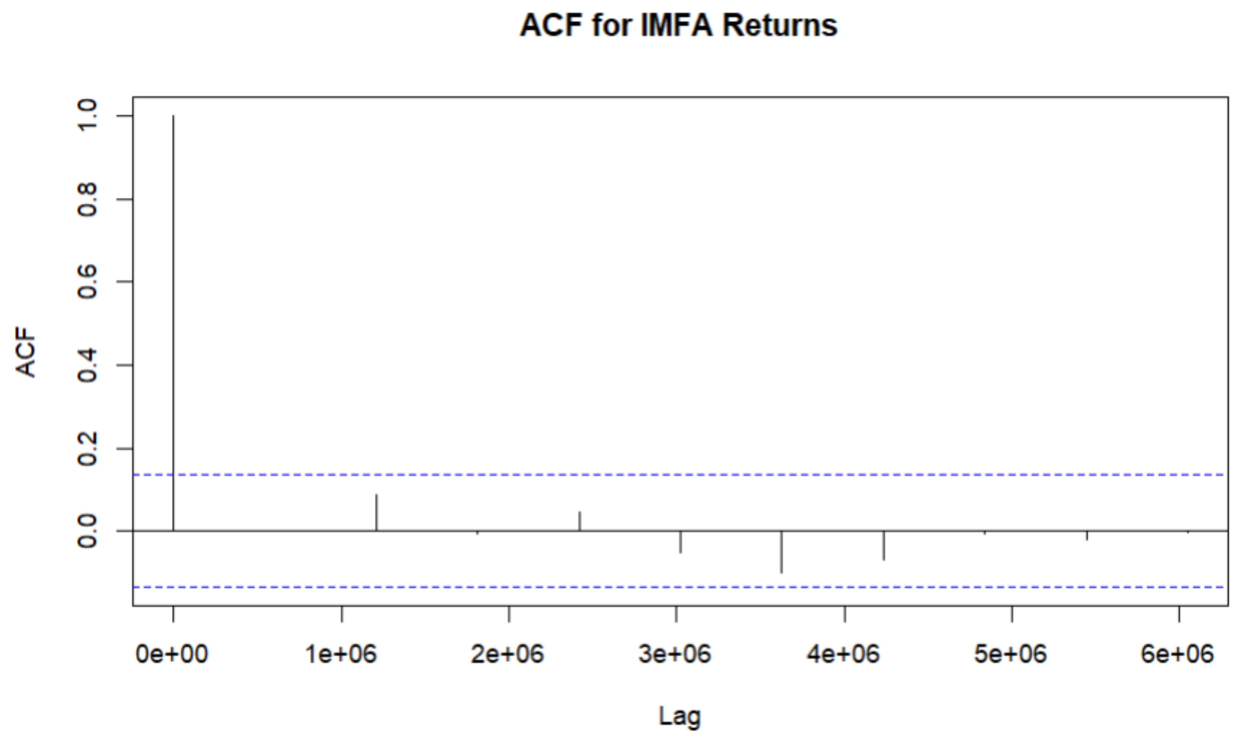
The AR and MA coefficient of the security can be estimated by using the ACF and PACF plot



An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The p-value resulting from the ADF test is 0.01 which is less than 0.05 or 5%. The experiments yielded the following results:

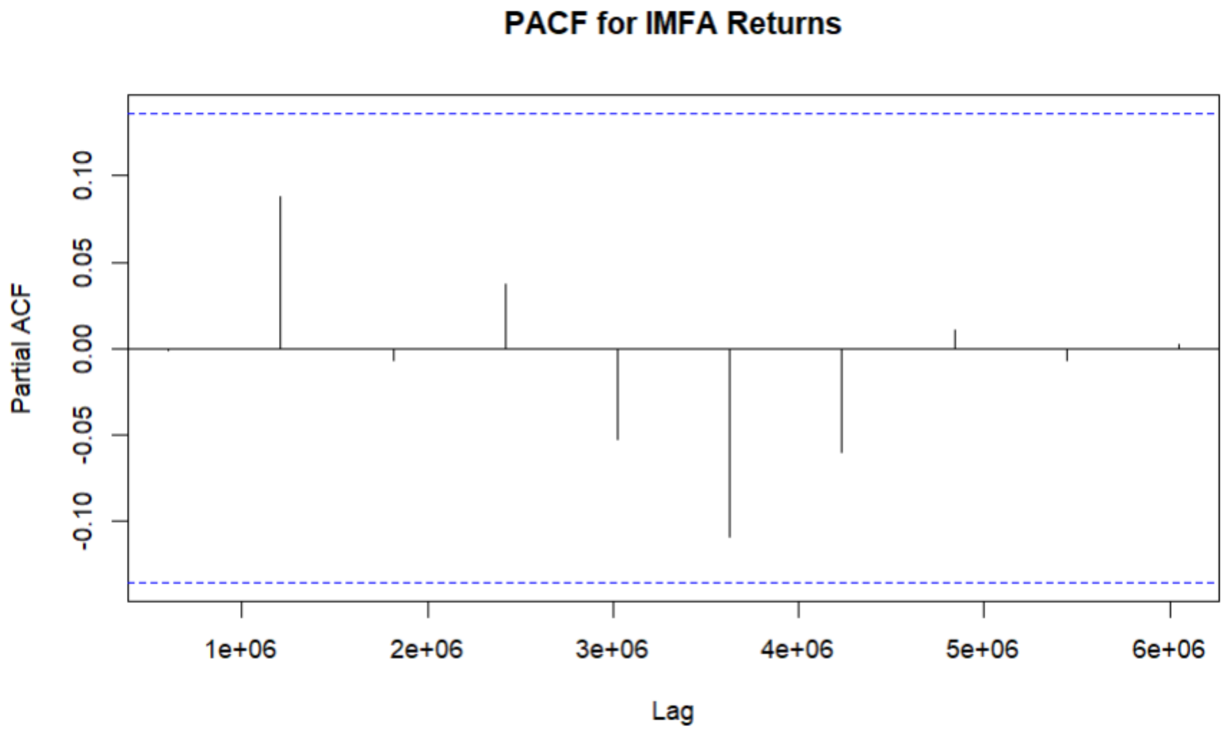
```
	Augmented Dickey-Fuller Test

data:  returns_IMFA
Dickey-Fuller = -6.4351, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

ACF Plot:



The ACF property specifies a unique autocorrelation sequence. The ACF exponentially decreases to zero as the latency h increases with a positive value of $\phi 1$. ACF decays exponentially to 0 as the latency increases for negative $\phi 1$, but algebraic signs for the autocorrelations fluctuate from positive to negative. As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot:



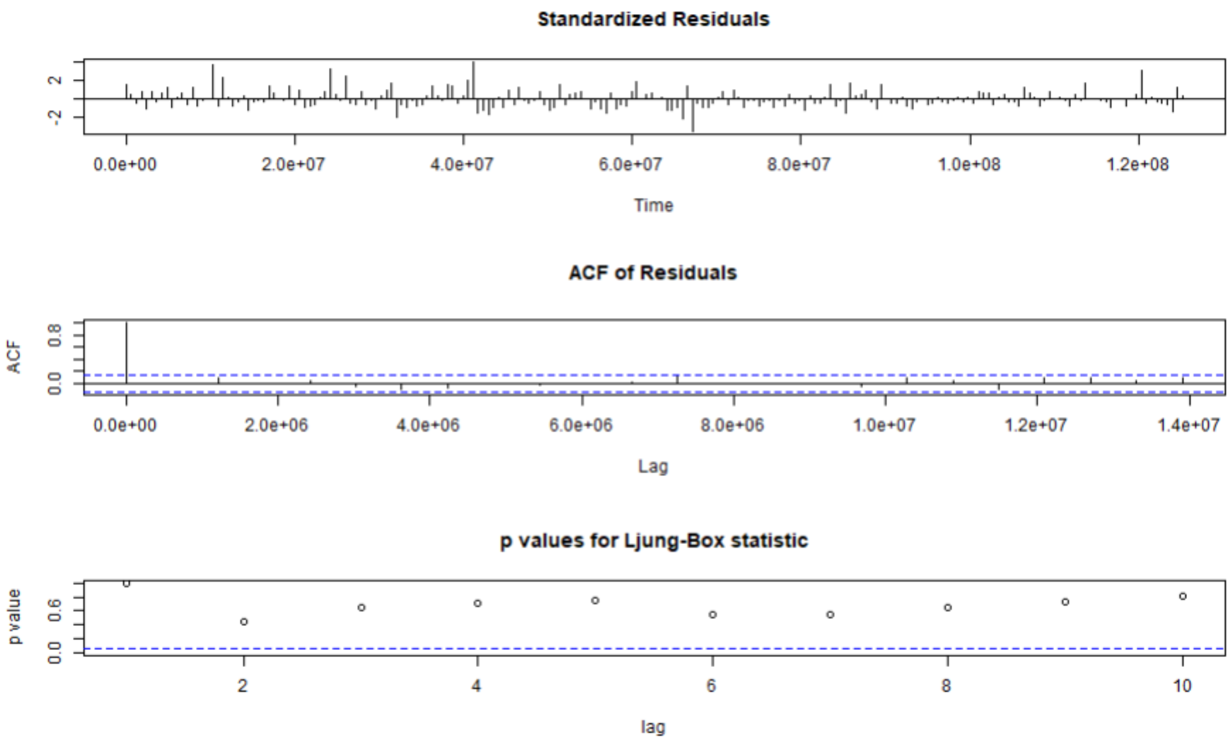
Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero.

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
Call:
arima(x = returns_IMFA, order = c(0, 0, 0))

Coefficients:
      intercept
         0.0140
s.e.     0.0047

sigma^2 estimated as 0.004689:  log likelihood = 262.57,  aic = -521.14

Training set error measures:
                       ME       RMSE        MAE      MPE    MAPE      MASE          ACF1
Training set 6.797667e-18 0.06847499 0.05060147 100.7711 180.811 0.6998594 -0.001037386
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test:



Interpretation :

The model's Standardized Residuals are distributed at random. For any value lag, the ACF of residuals is not important. Ljung-Box p-values are often greater than 0.05. As a result, we can infer that the model is a strong match based on the above three observations.

Prediction using ARIMA Model :

```
> predicted_IMFA
          Point Forecast       Lo 80     Hi 80     Lo 95    Hi 95
125798401     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
126403201     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
127008001     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
127612801     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
128217601     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
128822401     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
129427201     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
130032001     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
130636801     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
131241601     0.01396247 -0.07379175 0.1017167 -0.120246 0.148171
> tsdiag(arima_final_IMFA)
```

-GARCH AND EGARCHE

By running the GARCH model on Weekly returns following results were obtained

-WEEKLY GARCHE

```
> 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
```

We can say from the above figure that GARCH(1,1) is the most appropriate model and the corresponding mean model ARFIMA(1,0,1) is chosen.

Now we can start by running the EGARCH model on the daily returns of e-GARCH Model.

-WEEKLY EGARCHE

```
> 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
```

From the above result, it can be seen that EGARCH(1,1) is the resulting model, and the corresponding ARFIMA (1,0,1) is taken. The results coincide with the GARCH model used before.

-GARCHE MODEL FITTING

```
> ugfit_IMFA

*---------------------------------*
*          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      0.012231    0.004254 2.8755e+00 0.004034
ar1    -0.834341    0.372741 -2.2384e+00 0.025196
ma1     0.804391    0.401319 2.0044e+00 0.045031
omega   0.000000    0.000005 1.0000e-06 0.999999
alpha1  0.000005    0.000008 6.1798e-01 0.536590
beta1   0.998758    0.000004 2.7348e+05 0.000000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.012231    0.004879 2.5071e+00 0.012171
ar1    -0.834341    0.359862 -2.3185e+00 0.020422
ma1     0.804391    0.391105 2.0567e+00 0.039714
omega   0.000000    0.000007 1.0000e-06 0.999999
alpha1  0.000005    0.000009 5.1649e-01 0.605513
beta1   0.998758    0.000004 2.4071e+05 0.000000

LogLikelihood : 303.7862

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

Akaike       -2.5236
Bayes        -2.4355
Shibata      -2.5249
```

```
Hannan-Quinn -2.4881

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic p-value
Lag[1]                     0.04083  0.8399
Lag[2*(p+q)+(p+q)-1][5]    0.54461  1.0000
Lag[4*(p+q)+(p+q)-1][9]    2.02627  0.9834
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                         statistic p-value
Lag[1]                       0.660  0.4165
Lag[2*(p+q)+(p+q)-1][5]      1.908  0.6403
Lag[4*(p+q)+(p+q)-1][9]      2.476  0.8413
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     1.063 0.500 2.000  0.3025
ARCH Lag[5]     1.305 1.440 1.667  0.6451
ARCH Lag[7]     1.500 2.315 1.543  0.8213

Nyblom stability test
------------------------------------
Joint Statistic:  14.3085
Individual Statistics:
mu     0.29191
ar1    0.05157
ma1    0.05055
omega  0.28028
```

```
alpha1 0.23789
beta1  0.23603

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           1.1001 0.2724
Negative Sign Bias  0.5675 0.5710
Positive Sign Bias  0.6563 0.5123
Joint Effect        3.6764 0.2986


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     25.86      0.13401
2    30     35.27      0.19577
3    40     42.31      0.33026
4    50     62.31      0.09601


Elapsed time : 0.09440613
```

Observations from the Diagnostic test for the GARCH model for Weekly Returns

● The resulting log-likelihood of the model is 303.7862.

● GARCH(1,1) and corresponding ARFIMA(1,0,1) are best for weekly returns.

● The ALPHA and Omega parameters are derived by a fitting process of the GARCHmodel. The model's minimal AIC and BIC values are used to describe best fit.

-EGARCHE MODEL FITTING

```
Informat· > egfit_IMFA
---------
          *---------------------------------*
Akaike    *          GARCH Model Fit        *
Bayes     *---------------------------------*
Shibata
Hannan-Qı Conditional Variance Dynamics
          -----------------------------------
Weighted  GARCH Model      : eGARCH(1,1)
--------- Mean Model       : ARFIMA(1,0,1)
          Distribution     : norm
Lag[1]
Lag[2*(p- Optimal Parameters
Lag[4*(p- ------------------------------------
d.o.f=2           Estimate  Std. Error  t value Pr(>|t|)
H0 : No s mu       0.014543    0.000005  3206.84        0
          ar1     -0.646357    0.001326  -487.31        0
Weighted  ma1      0.632124    0.000864   731.57        0
--------- omega   -0.122848    0.000027 -4609.81        0
          alpha1   0.055730    0.000010  5835.08        0
Lag[1]    beta1    0.977854    0.000152  6448.77        0
Lag[2*(p- gamma1  -0.117599    0.000044 -2664.70        0
Lag[4*(p-
d.o.f=2   Robust Standard Errors:
                  Estimate  Std. Error  t value Pr(>|t|)
Weighted  mu       0.014543    0.000065  225.111        0
--------- ar1     -0.646357    0.014939  -43.266        0
          ma1      0.632124    0.011455   55.185        0
ARCH Lag| omega   -0.122848    0.000552 -222.549        0
ARCH Lag| alpha1   0.055730    0.000082  679.273        0
ARCH Lag| beta1    0.977854    0.006347  154.060        0
          gamma1  -0.117599    0.000794 -148.161        0
Nyblom st
--------- LogLikelihood : 318.9415
```

```
Nyblom stability test
------------------------------------
Joint Statistic:  5.766
Individual Statistics:
mu     0.07126
ar1    0.15788
ma1    0.13736
omega  0.07074
alpha1 0.07100
beta1  0.38628
gamma1 0.07787

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           1.5195 0.1300
Negative Sign Bias  1.0992 0.2728
Positive Sign Bias  0.6193 0.5363
Joint Effect        2.3936 0.4948


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     22.98      0.23809
2    30     48.24      0.01389
3    40     53.83      0.05736
4    50     72.90      0.01498


Elapsed time : 0.250051
```

The log-likelihood of the model stands at 318.9415. For IGL returns, the optimal models identified are eGARCH(1,1) coupled with ARFIMA(1,0,1).

- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected

and hence the observed values and expected values do not differ by a lot.

MONTHLY RETURNS

CAPM

```
Call:
lm(formula = exStock ~ exNSE, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.40144 -0.09720 -0.02516  0.06687  0.58384

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.05973    0.06576   0.908    0.368
exNSE        1.04981    0.15119   6.944 5.56e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1627 on 53 degrees of freedom
Multiple R-squared:  0.4764,    Adjusted R-squared:  0.4665
F-statistic: 48.21 on 1 and 53 DF,  p-value: 5.558e-09
```

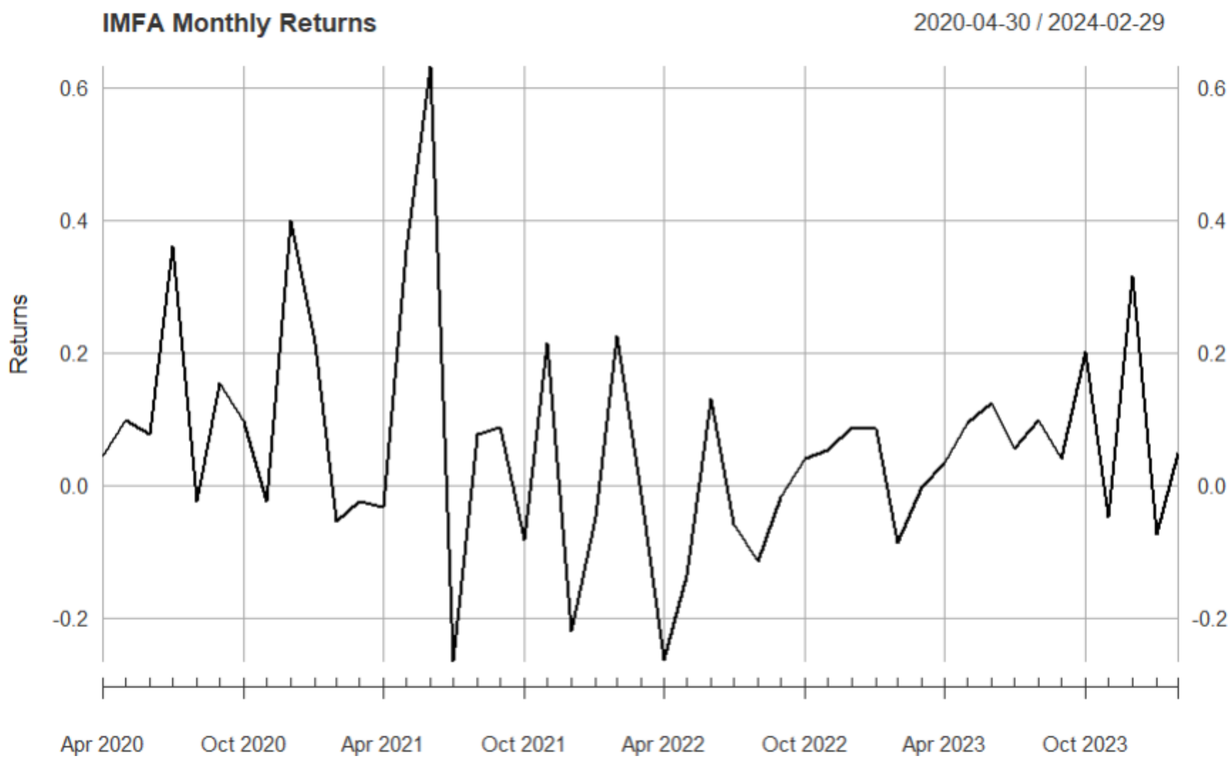
Monthly Returns (Beta = 1.04981)

Interpretation:

On a monthly basis, IMFA has a beta of 1.04981, which increases its volatility in long term. This means that from an investment perspective, even though the stock is a bit less sensitive across short periods, it is more extremely sensitive when viewed through a lens of long-term investments.

Estimating AR and MA coefficient using ARIMA model

The AR and MA coefficient of the security can be estimated by using the ACF and PACF plots.

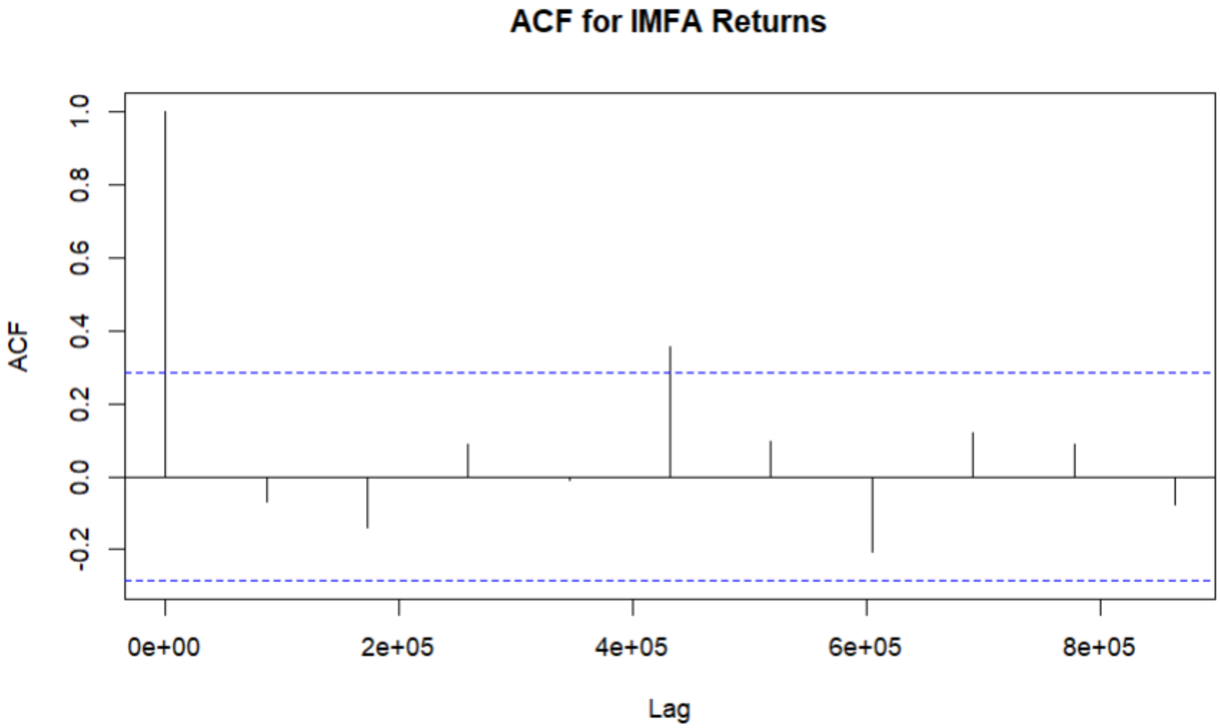


The variance of returns is constant for the analysis period. An Augmented Dickey-Fuller test was used to confirm that the sequence was stationary. The experiments yielded the following results:

```
        Augmented Dickey-Fuller Test

data:  returns_IMFA
Dickey-Fuller = -3.4093, Lag order = 3, p-value = 0.06634
alternative hypothesis: stationary
```

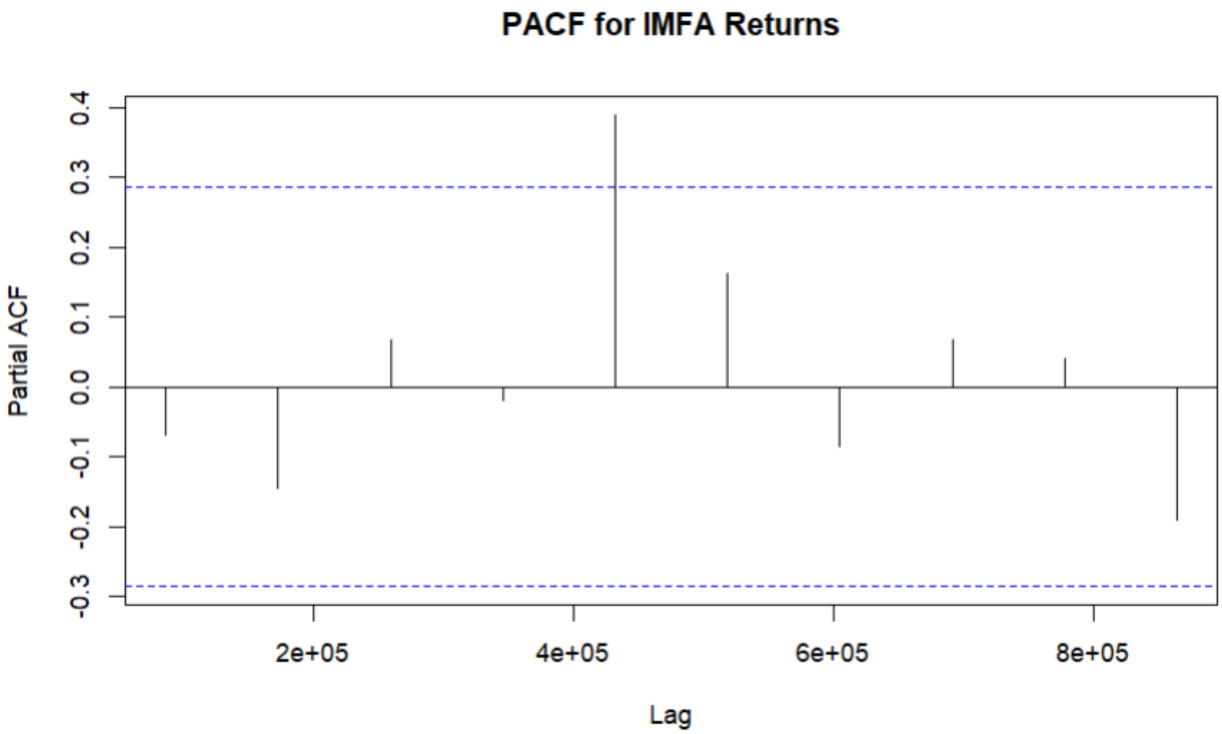
The p – value from the Augmented Dickey-Fuller Test is greater than 0.05 which shows that the series is not stationary.

ACF Plot:



The ACF demonstrates a sharp drop to near-zero values as the lag increases. For most other lags, the autocorrelations are close to zero and lie within the confidence intervals, indicating that there is no significant autocorrelation.As the ACF is not significant for any value of lag, the order of the moving average model is 0. Estimated to be MA (0) model.

PACF Plot :



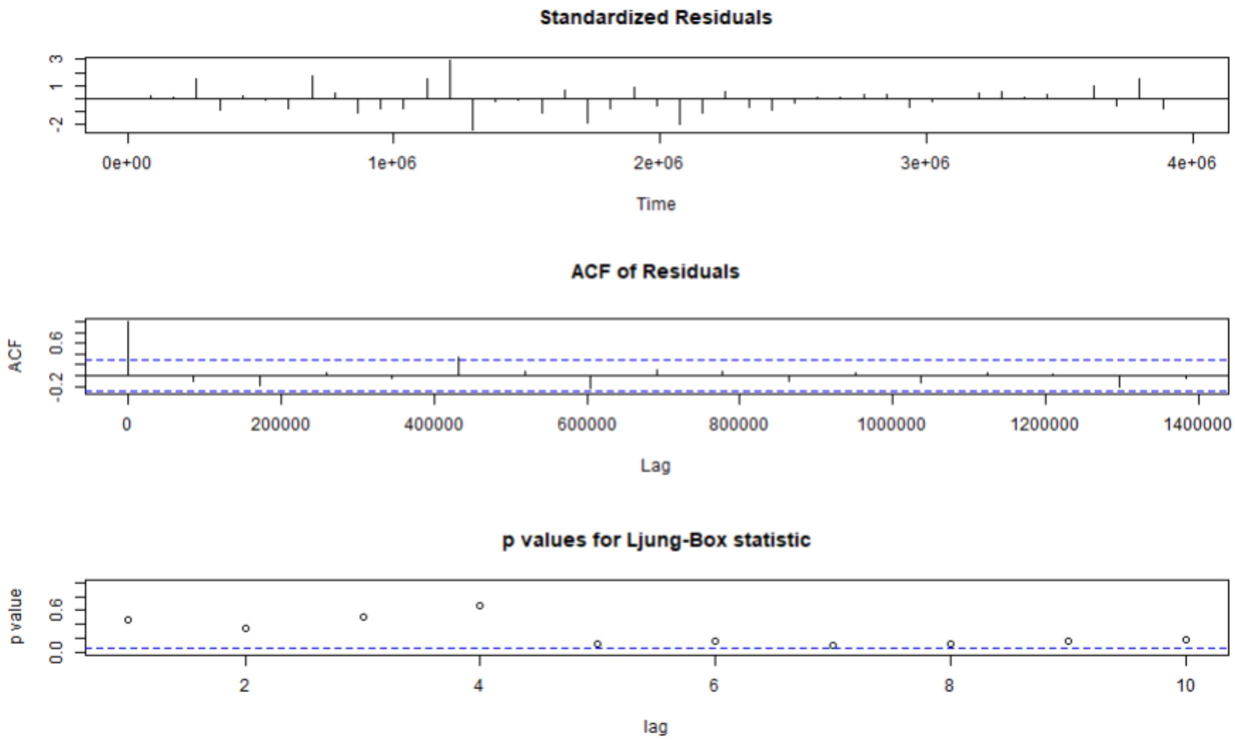
Autocorrelation for all the lags are statistically unsignificant. This suggests a possible AR (0) model for these data. As can be seen from the graph above that the PACF is not significant for any value of lag, the order of the auto regressive model can be taken as zero

Following this, ARIMA model was run on all the orders(p,d,q). The best model is the one which has the least AIC value.

```
> summary(arima_final_IMFA)

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

Coefficients:
          ma1
      -0.9399
s.e.   0.1003

sigma^2 estimated as 0.02968:  log likelihood = 14.56,  aic = -25.11

Training set error measures:
                      ME      RMSE       MAE      MPE     MAPE      MASE       ACF1
Training set -0.01578528 0.1704291 0.1261484 165.9108 172.0238 0.6875555 -0.1044649
```

After running various (p,d,q) models we see that the least value of AIC is for the (0,0,0) which is what we estimated from ACF and PACF models.

Diagnostic Test :



Interpretation :

The model's Residuals are distributed at random . For any value lag the ACF of residual is not important. Ljung-Box p-values are often smaller than 0.05. As a result , we can infer that the model is a strong match based on the above three observations

Prediction using ARIMA Model :

```
> predicted_IMFA
        Point Forecast      Lo 80     Hi 80      Lo 95     Hi 95
4060801     0.05535412 -0.1654589 0.2761672 -0.2823503 0.3930585
4147201     0.05535412 -0.1658571 0.2765654 -0.2829593 0.3936675
4233601     0.05535412 -0.1662546 0.2769628 -0.2835672 0.3942754
4320001     0.05535412 -0.1666514 0.2773596 -0.2841740 0.3948822
4406401     0.05535412 -0.1670474 0.2777557 -0.2847797 0.3954879
4492801     0.05535412 -0.1674428 0.2781510 -0.2853844 0.3960926
4579201     0.05535412 -0.1678374 0.2785457 -0.2859879 0.3966962
4665601     0.05535412 -0.1682314 0.2789396 -0.2865904 0.3972987
4752001     0.05535412 -0.1686247 0.2793329 -0.2871919 0.3979001
4838401     0.05535412 -0.1690173 0.2797255 -0.2877923 0.3985005
> tsdiag(arima_final_IMFA)
```

Garche & EGarche

```
> ugfit_IMFA

*---------------------------------*
*          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      0.057856    0.021124   2.7389 0.006164
ar1    -0.895975    0.059479 -15.0637 0.000000
ma1     1.000000    0.042628  23.4589 0.000000
omega   0.002406    0.001428   1.6852 0.091944
alpha1  0.135526    0.089661   1.5115 0.130652
beta1   0.759572    0.077523   9.7980 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.057856    0.023896   2.42119 0.015470
ar1    -0.895975    0.066560 -13.46108 0.000000
ma1     1.000000    0.076671  13.04281 0.000000
omega   0.002406    0.005327   0.45159 0.651565
alpha1  0.135526    0.147197   0.92071 0.357200
beta1   0.759572    0.275133   2.76074 0.005767

LogLikelihood : 25.56217

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

```
------------------------------------

Akaike       -0.72452
Bayes        -0.50353
Shibata      -0.74608
Hannan-Quinn -0.63929

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.5646  0.4524
Lag[2*(p+q)+(p+q)-1][5]    1.6414  0.9942
Lag[4*(p+q)+(p+q)-1][9]    5.0066  0.4521
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.442  0.2298
Lag[2*(p+q)+(p+q)-1][5]     4.348  0.2137
Lag[4*(p+q)+(p+q)-1][9]     6.857  0.2114
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     2.961 0.500 2.000  0.0853
ARCH Lag[5]     4.173 1.440 1.667  0.1589
ARCH Lag[7]     5.025 2.315 1.543  0.2220

Nyblom stability test
------------------------------------
Joint Statistic:  1.1867
Individual Statistics:
mu     0.43702
ar1    0.06045
ma1    0.07635
omega  0.35500
```

```
alpha1 0.22630
beta1  0.37509

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            2.546 0.01409  **
Negative Sign Bias   1.647 0.10601
Positive Sign Bias   2.196 0.03284  **
Joint Effect         8.265 0.04084  **


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     16.37      0.63244
2    30     40.44      0.07693
3    40     42.30      0.33060
4    50     55.26      0.25018


Elapsed time : 0.09343314
```

- The Log-likelihood of the model is 25.56217. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-EGarche Modelling IMFA

```
LogLikelih > egfit_IMFA

Informatic *---------------------------------*
---------- *          GARCH Model Fit        *
           *---------------------------------*
Akaike
Bayes      Conditional Variance Dynamics
Shibata    -----------------------------------
Hannan-Qui GARCH Model      : eGARCH(1,1)
           Mean Model       : ARFIMA(1,0,1)
Weighted L Distribution     : norm
----------
           Optimal Parameters
Lag[1]     ------------------------------------
Lag[2*(p+c         Estimate  Std. Error  t value Pr(>|t|)
Lag[4*(p+c mu      0.039629    0.000015   2697.3        0
d.o.f=2    ar1     0.459870    0.000142   3229.4        0
H0 : No se ma1    -0.425857    0.000173  -2465.3        0
           omega  -0.408856    0.000066  -6216.5        0
Weighted L alpha1  0.187403    0.000103   1814.6        0
---------- beta1   0.911709    0.000181   5026.4        0
           gamma1 -0.654010    0.000226  -2898.0        0
Lag[1]
Lag[2*(p+c Robust Standard Errors:
Lag[4*(p+c         Estimate  Std. Error  t value Pr(>|t|)
d.o.f=2    mu      0.039629    0.000071   560.97        0
           ar1     0.459870    0.001031   445.96        0
Weighted A ma1    -0.425857    0.000754  -564.96        0
---------- omega  -0.408856    0.000649  -629.94        0
           alpha1  0.187403    0.000190   988.91        0
ARCH Lag[3 beta1   0.911709    0.001363   668.80        0
ARCH Lag[5 gamma1 -0.654010    0.000272 -2406.75        0
ARCH Lag[7]

Nyblom stability test
------------------------------------
```

```
------------------------------------
Joint Statistic:  1.6131
Individual Statistics:
mu     0.01336
ar1    0.01375
ma1    0.01376
omega  0.01345
alpha1 0.01345
beta1  0.01921
gamma1 0.01349

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           1.6403 0.1074
Negative Sign Bias  0.6551 0.5155
Positive Sign Bias  1.0267 0.3096
Joint Effect        3.0125 0.3897


Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     28.22      0.07924
2    30     30.44      0.39207
3    40     43.78      0.27586
4    50     57.11      0.19917


Elapsed time : 0.217675
```

- The Log-likelihood of the model is 35.85142. eGARCH(1,1) and corresponding ARFIMA(1,0,1) are best.
- In the Ljung-box test result section, since all the p-values for both Standardized results and standard squared residuals are much higher than 0.05, the null hypothesis cannot be rejected and hence no serial autocorrelation exists which is a good condition for the model.
- In the Adjusted Pearson goodness-of-fit section, all the p-values are very high, which implies that the null hypothesis cannot be rejected and hence the observed values and expected values do not differ by a lot.

-Forecasting using Garche

```
> ugforecast_IMFA

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

0-roll forecast [T0=2024-08-31]:
      Series  Sigma
T+1   0.08983 0.1242
T+2   0.02921 0.1273
T+3   0.08353 0.1301
T+4   0.03486 0.1325
T+5   0.07846 0.1346
T+6   0.03939 0.1364
T+7   0.07440 0.1381
T+8   0.04303 0.1396
T+9   0.07114 0.1408
T+10  0.04596 0.1420
```

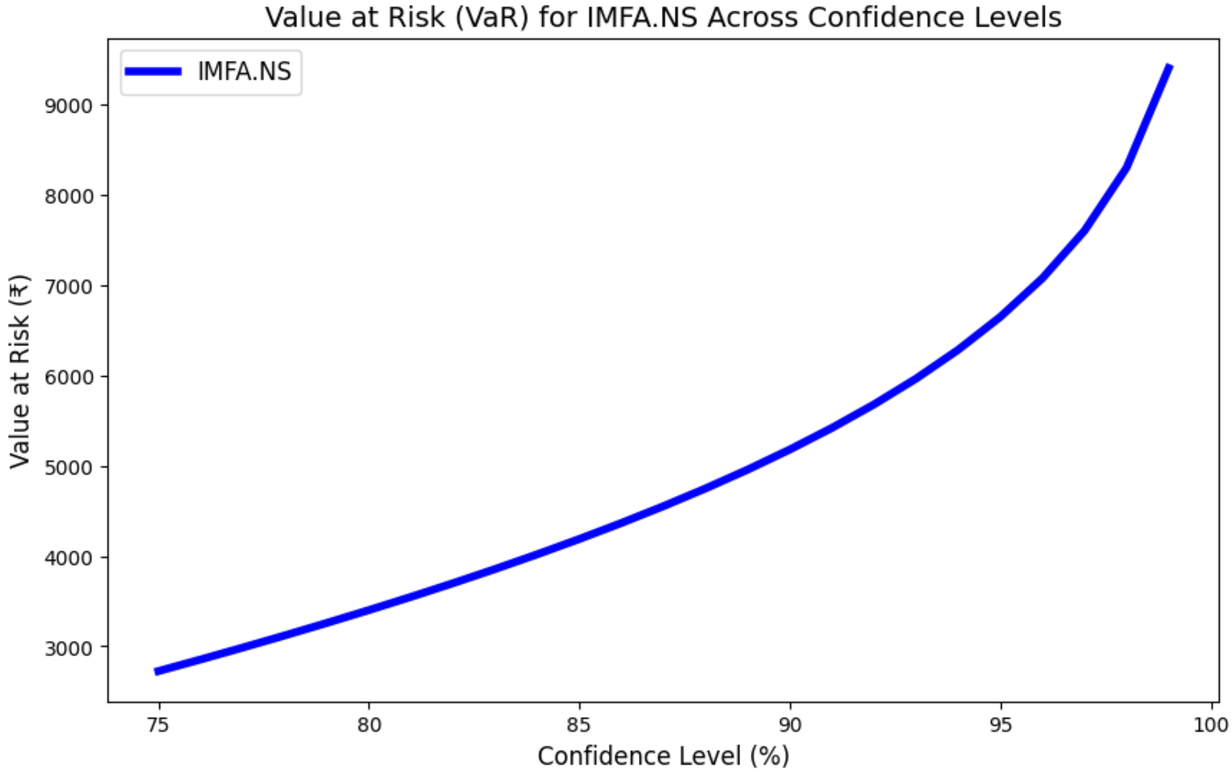
The above table shows the forecasted value using the GARCH model for the monthly return.

-Forecasting using EGarche

```
> egforecast_IMFA

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

0-roll forecast [T0=2024-08-31]:
      Series   Sigma
T+1  0.03753 0.06865
T+2  0.03866 0.07089
T+3  0.03918 0.07299
T+4  0.03942 0.07497
T+5  0.03954 0.07681
T+6  0.03959 0.07853
T+7  0.03961 0.08014
T+8  0.03962 0.08163
T+9  0.03962 0.08301
T+10 0.03963 0.08429
```

The result of forecasting is shown in Figure . The results show that the returns fluctuate for the next 10 days, with a mean value of 3.89% and a standard deviation of 6.1%.

Calculating Value at Risk For IMFA:-



Value at Risk (VaR) calculates the possible decline in the value of an investment or portfolio over a given period of time, assuming a particular degree of confidence (e.g., 95% or 99%).It helps investors and institutions comprehend the worst-case scenario under typical market conditions by giving them a measurable indicator of downside risk.

Above is the graph for IMFA, showing the value at risk at different confidence intervals from 75% to 100%. At 75% confidence level, VaR is 3,000, which means that there is only a 25% chance that the stock price will fall by 3,000 rupees in a day. Similarly, VaR at 95% confidence level is 7,000, which means that there is only a 5% chance that the stock price will fall by 7,000 rupees in a day. At 100% confidence level, there is no chance that the stock price will fall by more than 9,000 rupees.