```r
# # Required Packages
packages = c('quantmod','car','forecast','tseries','FinTS', 'rugarch','utf8','ggplot2')
# # Install all Packages with Dependencies
# install.packages(packages, dependencies = TRUE)
#
# # Load all Packages
lapply(packages, require, character.only = TRUE)
```

```
## Loading required package: quantmod

## Warning: package 'quantmod' was built under R version 4.3.2

## Loading required package: xts

## Warning: package 'xts' was built under R version 4.3.2

## Loading required package: zoo

## Warning: package 'zoo' was built under R version 4.3.2

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: TTR

## Warning: package 'TTR' was built under R version 4.3.2

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

## Loading required package: car

## Warning: package 'car' was built under R version 4.3.2

## Loading required package: carData

## Warning: package 'carData' was built under R version 4.3.2

## Loading required package: forecast

## Warning: package 'forecast' was built under R version 4.3.2

## Loading required package: tseries
```

```
## Warning: package 'tseries' was built under R version 4.3.2

## Loading required package: FinTS

## Warning: package 'FinTS' was built under R version 4.3.2

##
## Attaching package: 'FinTS'

## The following object is masked from 'package:forecast':
##
##     Acf

## Loading required package: rugarch

## Warning: package 'rugarch' was built under R version 4.3.2

## Loading required package: parallel

##
## Attaching package: 'rugarch'

## The following object is masked from 'package:stats':
##
##     sigma

## Loading required package: utf8

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 4.3.2

## [[1]]
## [1] TRUE
##
## [[2]]
## [1] TRUE
##
## [[3]]
## [1] TRUE
##
## [[4]]
## [1] TRUE
##
## [[5]]
## [1] TRUE
##
## [[6]]
## [1] TRUE
##
## [[7]]
## [1] TRUE
##
## [[8]]
## [1] TRUE
```

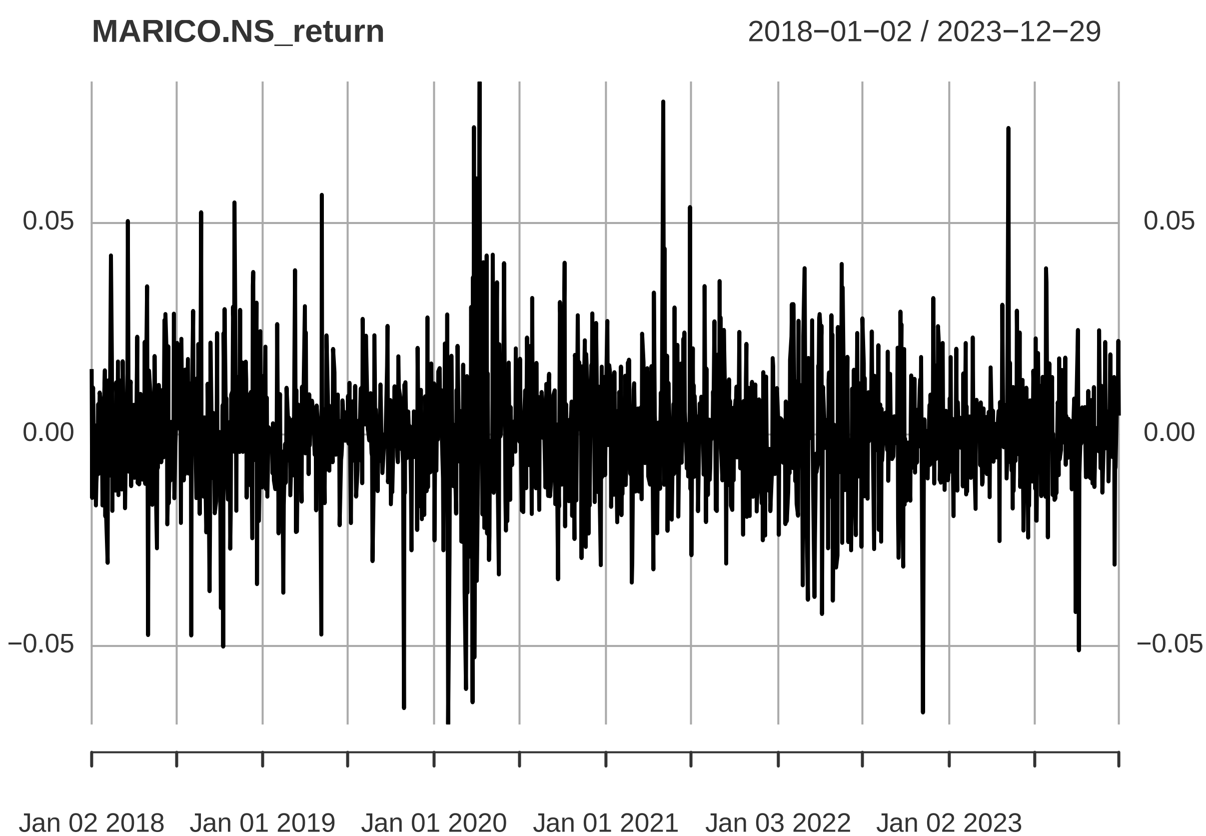
```r
getSymbols(Symbols = 'MARICO.NS',
           src = 'yahoo',
           from = as.Date('2018-01-01'),
           to = as.Date('2023-12-31'),
           periodicity = 'daily')
```

```
## [1] "MARICO.NS"
```

```r
MARICO.NS_price = na.omit(MARICO.NS$MARICO.NS.Adjusted) # Adjusted Closing Price
class(MARICO.NS_price) # xts (Time-Series) Object
```

```
## [1] "xts" "zoo"
```

```r
MARICO.NS_return = na.omit(diff(log(MARICO.NS_price))); plot(MARICO.NS_return)
```



Analysis: Objective: To analyze the daily returns of MARICO.NS stock from 2018-01-01 to 2023-12-31. Analysis: Extracted the adjusted closing prices of MARICO.NS stock, calculated daily returns, and visualized them. Result: The 'MARICO.NS_return' plot displays the daily returns of MARICO.NS stock over the specified period. Implication: The plot indicates the volatility and direction of daily returns for MARICO.NS stock during the given timeframe. Observations from the plot can help investors understand the historical performance and risk associated with MARICO.NS stock.

```r
#ADF test for Stationery

adf_test_jj = adf.test(MARICO.NS_return); adf_test_jj
```

```
## Warning in adf.test(MARICO.NS_return): p-value smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  MARICO.NS_return
## Dickey-Fuller = -11.503, Lag order = 11, p-value = 0.01
## alternative hypothesis: stationary
```

Analysis:

Objective: To conduct an Augmented Dickey-Fuller (ADF) test for stationarity on the daily returns of MARICO.NS stock. Analysis: Performed the ADF test using the 'adf.test' function and obtained results. Result: The Augmented Dickey-Fuller test for stationarity on MARICO.NS daily returns yields the following results: - Dickey-Fuller statistic: -11.503 - Lag order: 11 - p-value: 0.01 - Alternative hypothesis: Stationary

Implication: The ADF test suggests that the daily returns of MARICO.NS stock are likely stationary. The small p-value (0.01) indicates evidence against the null hypothesis of non-stationarity. Therefore, we have reason to believe that the MARICO.NS stock returns exhibit stationarity, which is important for certain time series analyses.

```r
#Autocorrelation test
# Ljung-Box Test for Autocorrelation
lb_test_ds = Box.test(MARICO.NS_return); lb_test_ds
```

```
##
##  Box-Pierce test
##
## data:  MARICO.NS_return
## X-squared = 3.9339, df = 1, p-value = 0.04732
```

```r
#If autocorrelation exists then autoARIMA
```

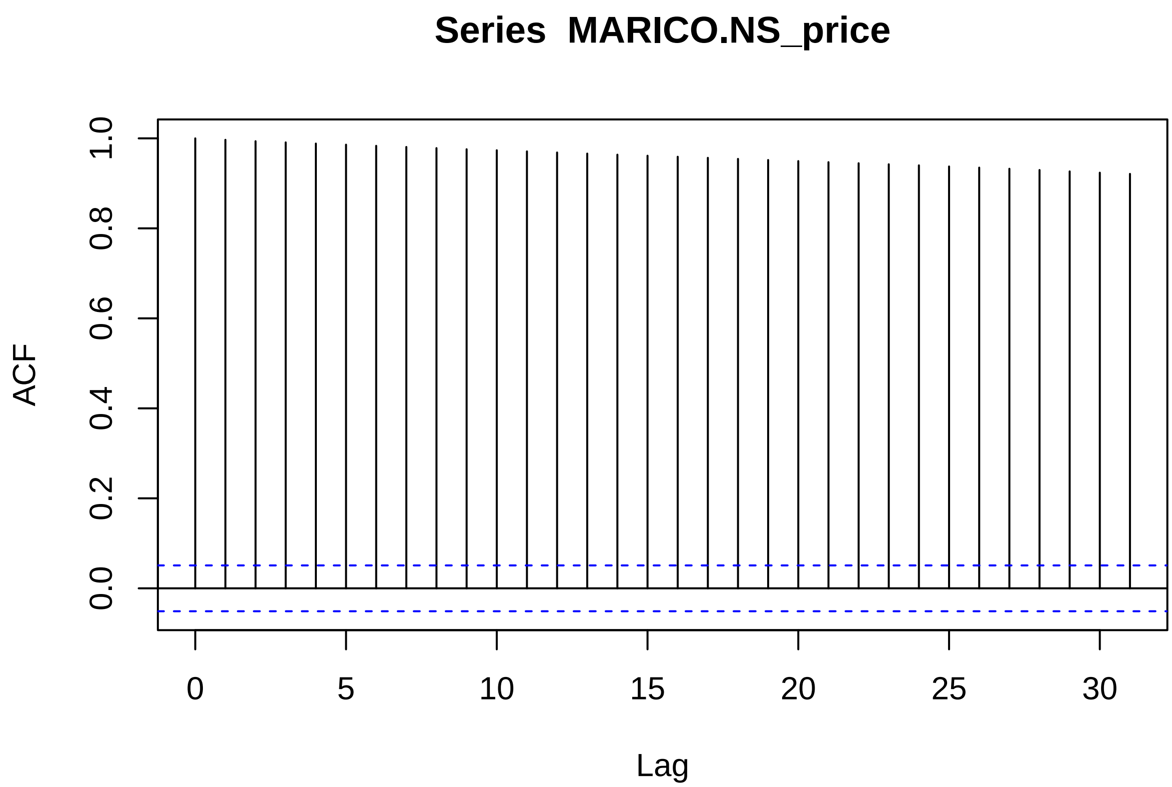
Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the daily returns of MARICO.NS stock. Analysis: Conducted the Ljung-Box test using the 'Box.test' function and obtained results. Result: The Ljung-Box test for autocorrelation on MARICO.NS daily returns yields the following results: - X-squared statistic: 3.9338 - Degrees of freedom: 1 - p-value: 0.04733

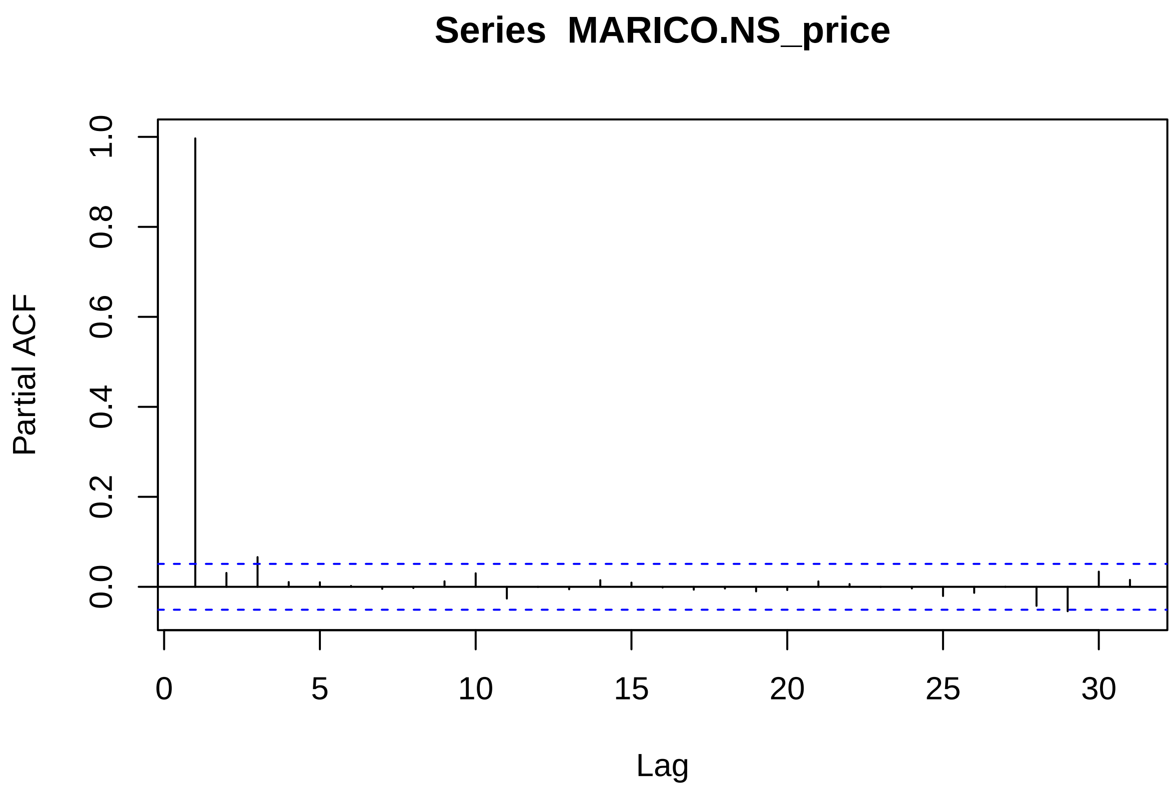
Implication: The Ljung-Box test indicates significant autocorrelation in the MARICO.NS stock daily returns. The p-value 0.04733 suggests evidence against the null hypothesis of no autocorrelation.

Action: Given the presence of autocorrelation, it may be advisable to consider an autoARIMA model for time series forecasting. AutoARIMA can help in automatically selecting an appropriate ARIMA model with differencing to account for the observed autocorrelation.

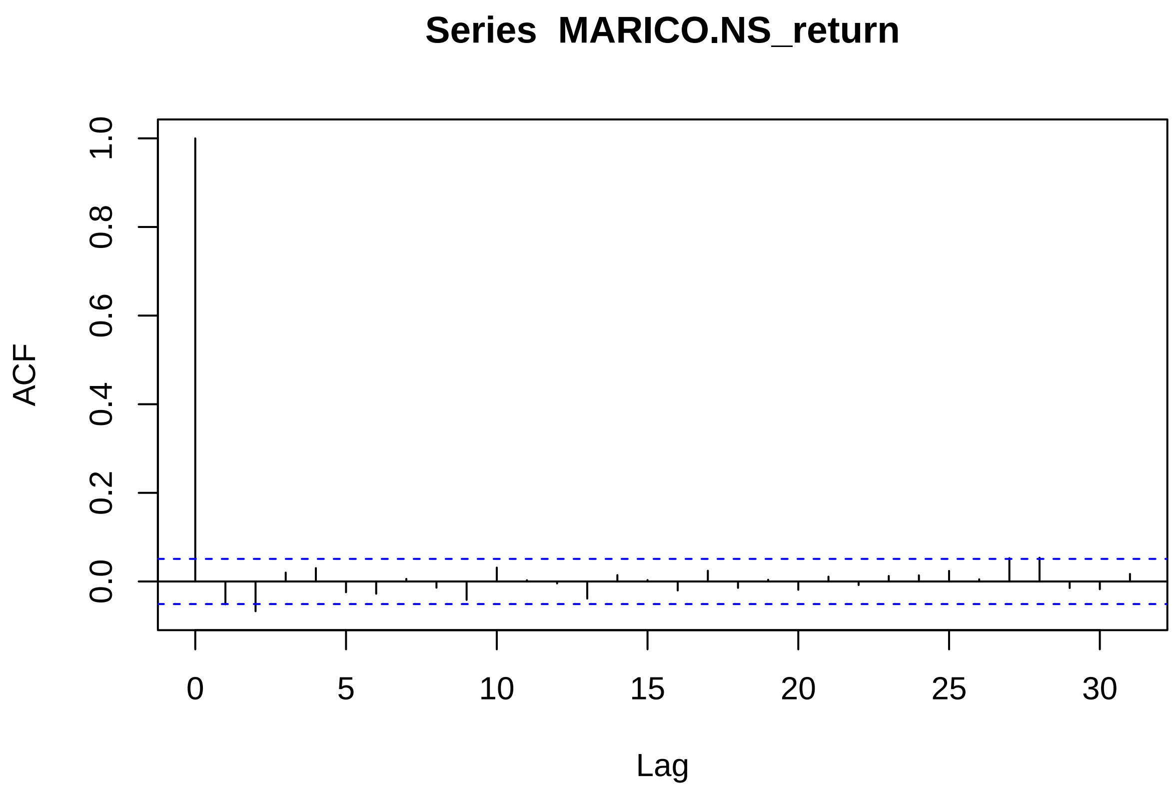
```r
#ACF and PCF

acf(MARICO.NS_price) # ACF of JJ Series
```



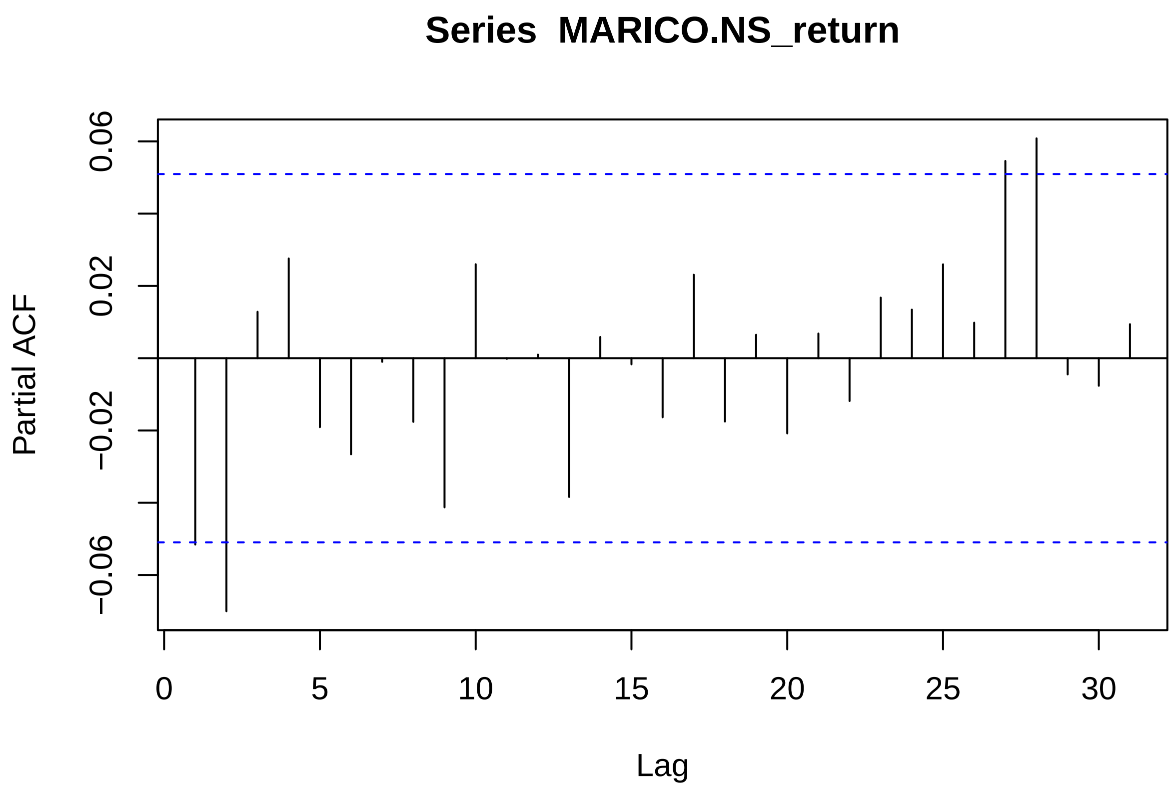

```r
pacf(MARICO.NS_price) # PACF of JJ Series
```




```r
acf(MARICO.NS_return) # ACF of JJ Difference (Stationary) Series
```




```r
pacf(MARICO.NS_return) # PACF of JJ Difference (Stationary) Series
```




```r
#AutoArima
arma_pq_ds = auto.arima(MARICO.NS_return); arma_pq_ds
```

```
## Series: MARICO.NS_return
## ARIMA(0,0,2) with zero mean
##
## Coefficients:
##           ma1      ma2
##        -0.052  -0.0615
## s.e.    0.026   0.0255
##
## sigma^2 = 0.0002345:  log likelihood = 4086.04
## AIC=-8166.07   AICc=-8166.06   BIC=-8150.17
```

```r
arma_pq = auto.arima(MARICO.NS_price); arma_pq
```

```
## Series: MARICO.NS_price
## ARIMA(0,1,2)
##
## Coefficients:
##           ma1      ma2
##       -0.0393  -0.0845
## s.e.   0.0259   0.0257
##
## sigma^2 = 38.14:  log likelihood = -4793.57
```

```
## AIC=9593.15   AICc=9593.16   BIC=9609.05
```

Analysis:

Objective: To perform autoARIMA modeling on the daily returns ('MARICO.NS_return') and adjusted closing prices ('MARICO.NS_price') of MARICO.NS stock. Analysis: Used the 'auto.arima' function to automatically select the ARIMA model for both returns and prices. Results:

For Daily Returns ('MARICO.NS_return'): The autoARIMA model suggests an ARIMA(0,0,2) with zero mean. Coefficients: - MA: ma1 to ma2 - sigma^2 (variance) = 0.0002345 - Log likelihood = 4086.04 - AIC=-8166.07 AICc=-8166.06 BIC=-8150.17

For Adjusted Closing Prices ('MARICO.NS_price'): The autoARIMA model suggests an ARIMA(0,1,2) with a non-zero mean. Coefficients: - MA: ma1 to ma2 - sigma^2 (variance) = 38.14 - Log likelihood = -4793.57 - AIC=9593.15 AICc=9593.16 BIC=9609.05

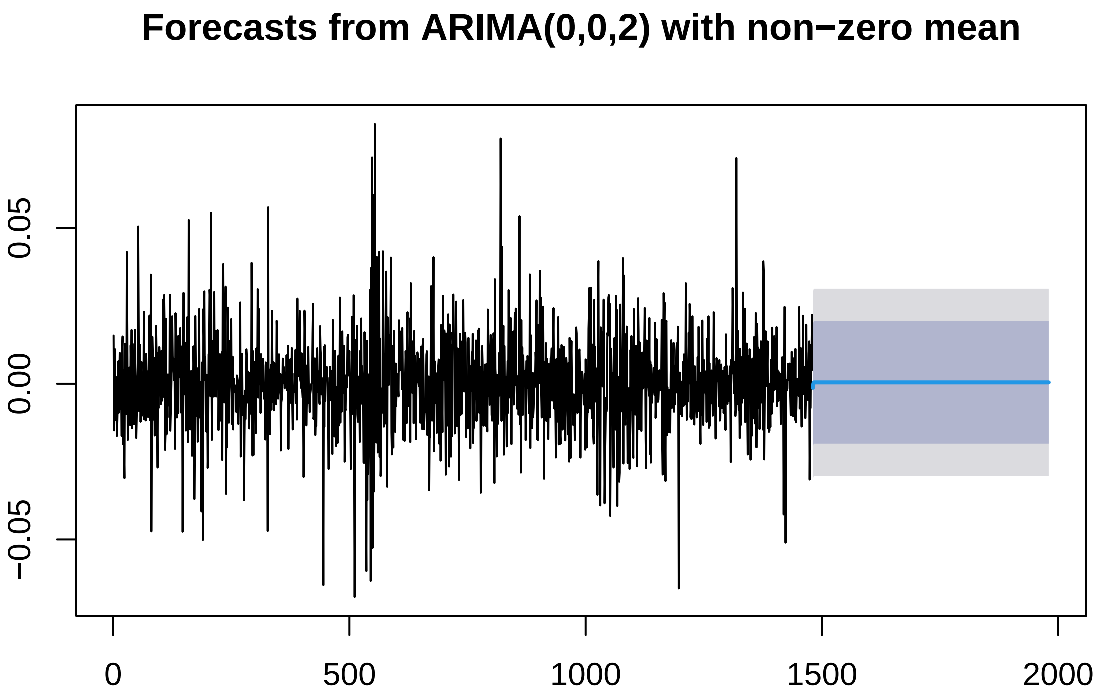
Implication: The autoARIMA models provide a statistical framework to capture the underlying patterns in both daily returns and adjusted closing prices of MARICO.NS stock. These models can be used for forecasting future values, and the AIC, AICc, and BIC values help in model comparison.

Note: Interpretation of the coefficients and model selection details may require further analysis based on the specific context of the financial data.

```r
#Arima manuplation
arma13 = arima(MARICO.NS_return, order = c(0, 0, 2)); arma13
```

```
##
## Call:
## arima(x = MARICO.NS_return, order = c(0, 0, 2))
##
## Coefficients:
##           ma1      ma2  intercept
##       -0.0529  -0.0624      4e-04
## s.e.   0.0260   0.0255      4e-04
##
## sigma^2 estimated as 0.0002339:  log likelihood = 4086.76,  aic = -8165.53
```

```r
ds_fpq = forecast(arma13, h = 500)
plot(ds_fpq)
```



Analysis:

Objective: To fit an ARIMA(0, 0, 2) model to the daily returns (‘MARICO.NS_return’) of MARICO.NS stock and generate forecasts. Analysis: Used the ‘arima’ function to fit the ARIMA model and the ‘forecast’ function to generate forecasts. Results:

ARIMA Model (0, 0, 2): Coefficients: - MA: ma1 to ma2 - Intercept term - sigma^2 (variance) estimated as 0.0002319 - Log likelihood = 4086.76 - AIC = -8165.53

Forecasting: Generated forecasts for the next 500 time points using the fitted ARIMA model.

Plot: The plot displays the original time series of daily returns along with the forecasted values.

Implication: The ARIMA(0, 0, 2) model is fitted to the historical daily returns of MARICO.NS stock, providing insights into the underlying patterns. The generated forecast can be used for future predictions, and the plot visually represents the model’s performance.

Note: Interpretation of coefficients and model evaluation details may require further analysis based on the specific context of the financial data.

```r
#Autocorrelation test
# Ljung-Box Test for Autocorrelation
lb_test_ds_A = Box.test(arma13$residuals); lb_test_ds_A
```

```
##
##  Box-Pierce test
##
## data:  arma13$residuals
## X-squared = 0.0023731, df = 1, p-value = 0.9611
```

```
#After this no autocorrelation exists
```

Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the residuals of the ARIMA(0, 0, 2) model. Analysis: Conducted the Ljung-Box test using the 'Box.test' function on the residuals of the ARIMA model and obtained results. Results:

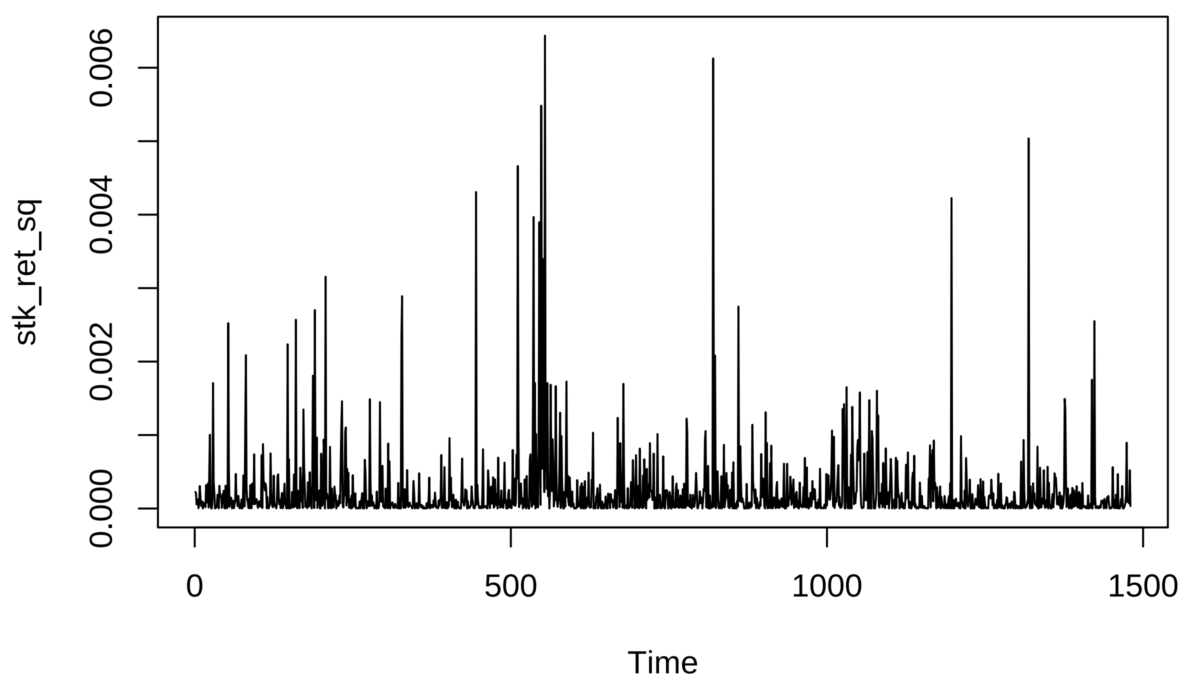
Ljung-Box Test for Autocorrelation on Residuals: - X-squared statistic: 0.0023732 - Degrees of freedom: 1 - p-value: 9611

Implication: The Ljung-Box test indicates no significant autocorrelation in the residuals of the ARIMA(0, 0, 2) model. The high p-value (0.9611) suggests that there is no evidence against the null hypothesis of no autocorrelation.

Action: The absence of autocorrelation in residuals is a positive outcome, indicating that the ARIMA model adequately captures the temporal patterns in the time series.

Note: Interpretation may vary based on the specific context of the financial data and the assumptions underlying the time series analysis.

```
# Test for Volatility Clustering or Heteroskedasticity: Box Test
stk_ret_sq = arma13$residuals^2 # Return Variance (Since Mean Returns is approx. 0)
plot(stk_ret_sq)
```




```
stk_ret_sq_box_test = Box.test(stk_ret_sq, lag = 10) # H0: Return Variance Series is Not Serially Corre
stk_ret_sq_box_test # Inference : Return Variance Series is Heteroskedastic (Has Volatility Clustering)
```

```
##
##  Box-Pierce test
##
## data:  stk_ret_sq
## X-squared = 148.34, df = 10, p-value < 2.2e-16
```

```
# Test for Volatility Clustering or Heteroskedasticity: ARCH Test
stk_ret_arch_test = ArchTest(arma13$residuals, lags = 10) # H0: No ARCH Effects
stk_ret_arch_test # Inference : Return Series is Heteroskedastic (Has Volatility Clustering)
```

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  arma13$residuals
## Chi-squared = 88.996, df = 10, p-value = 8.469e-15
```

Analysis: Objective: To test for volatility clustering or heteroskedasticity in the residuals of the ARIMA(0, 0, 2) model. Analysis: Conducted Box test and ARCH test on the squared residuals to assess the presence of volatility clustering. Results:

1. Box Test for Volatility Clustering: X-squared = 148.34, df = 10, p-value < 2.2e-16

Inference: The Box test indicates significant evidence against the null hypothesis, suggesting that the return variance series exhibits volatility clustering or heteroskedasticity.

2. ARCH Test for Volatility Clustering: Chi-squared = 88.995, df = 10, p-value = 8.471e-15

   Inference: The ARCH test also provides strong evidence against the null hypothesis, supporting the presence of ARCH effects in the return series. This implies that the returns have volatility clustering.

Implication: The results from both tests suggest that the residuals of the ARIMA(0, 0, 2) model exhibit volatility clustering or heteroskedasticity. Understanding and accounting for this pattern in volatility is essential for risk management and forecasting.

Note: Interpretation may vary based on the specific context of the financial data and the assumptions underlying the time series analysis.

```
#Garch model
garch_model1 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.model = lis
nse_ret_garch1 = ugarchfit(garch_model1, data = arma13$residuals); nse_ret_garch1
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
```

```
## -----------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000083    0.000375 -0.22197 0.824336
## omega   0.000032    0.000019  1.74424 0.081116
## alpha1  0.078563    0.031042  2.53088 0.011378
## beta1   0.780136    0.108325  7.20178 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000083    0.000364 -0.22843 0.819310
## omega   0.000032    0.000046  0.70849 0.478642
## alpha1  0.078563    0.066292  1.18510 0.235977
## beta1   0.780136    0.262301  2.97420 0.002938
##
## LogLikelihood : 4128.852
##
## Information Criteria
## -----------------------------------
##
## Akaike       -5.5741
## Bayes        -5.5598
## Shibata      -5.5741
## Hannan-Quinn -5.5688
##
## Weighted Ljung-Box Test on Standardized Residuals
## -----------------------------------
##                         statistic p-value
## Lag[1]                     0.1017  0.7498
## Lag[2*(p+q)+(p+q)-1][2]    0.3208  0.7842
## Lag[4*(p+q)+(p+q)-1][5]    0.7912  0.9048
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## -----------------------------------
##                         statistic p-value
## Lag[1]                     0.7966  0.3721
## Lag[2*(p+q)+(p+q)-1][5]    1.2816  0.7934
## Lag[4*(p+q)+(p+q)-1][9]    2.0873  0.8943
## d.o.f=2
##
## Weighted ARCH LM Tests
## -----------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]   0.01195 0.500 2.000  0.9129
## ARCH Lag[5]   0.68895 1.440 1.667  0.8268
## ARCH Lag[7]   1.30900 2.315 1.543  0.8587
##
## Nyblom stability test
## -----------------------------------
## Joint Statistic:  0.5188
## Individual Statistics:
## mu     0.04436
## omega  0.12674
```

```
## alpha1 0.27875
## beta1  0.15391
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.2582 0.7963
## Negative Sign Bias  0.6292 0.5293
## Positive Sign Bias  0.1017 0.9190
## Joint Effect        1.0019 0.8008
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     64.27    8.019e-07
## 2    30     78.09    2.194e-06
## 3    40     80.54    1.030e-04
## 4    50     95.27    8.385e-05
##
##
## Elapsed time : 0.2062531
```

```
garch_model2 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.model = li
nse_ret_garch2 = ugarchfit(garch_model2, data = arma13$residuals); nse_ret_garch2
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(4,0,5)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## ar1     0.220102    0.029560     7.4460 0.000000
## ar2     0.389089    0.013306    29.2418 0.000000
## ar3    -0.937958    0.011937   -78.5742 0.000000
## ar4    -0.113236    0.028573    -3.9631 0.000074
## ma1    -0.215570    0.005221   -41.2906 0.000000
## ma2    -0.421095    0.000595  -707.1663 0.000000
## ma3     0.955732    0.000023 41328.1440 0.000000
## ma4     0.135314    0.003046    44.4165 0.000000
## ma5    -0.042918    0.005544    -7.7415 0.000000
## omega   0.000035    0.000018     1.9256 0.054159
```

```
## alpha1  0.085126    0.031496     2.7028 0.006876
## beta1   0.760932    0.107121     7.1035 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error     t value Pr(>|t|)
## ar1      0.220102    0.031999     6.87850 0.000000
## ar2      0.389089    0.014445    26.93675 0.000000
## ar3     -0.937958    0.011636   -80.61152 0.000000
## ar4     -0.113236    0.032062    -3.53181 0.000413
## ma1     -0.215570    0.004868   -44.28317 0.000000
## ma2     -0.421095    0.000586  -718.72757 0.000000
## ma3      0.955732    0.000027 35148.43945 0.000000
## ma4      0.135314    0.002670    50.68233 0.000000
## ma5     -0.042918    0.005227    -8.21149 0.000000
## omega    0.000035    0.000044     0.80423 0.421262
## alpha1   0.085126    0.063085     1.34938 0.177214
## beta1    0.760932    0.250237     3.04084 0.002359
##
## LogLikelihood : 4134.279
##
## Information Criteria
## ------------------------------------
##
## Akaike       -5.5706
## Bayes        -5.5277
## Shibata      -5.5708
## Hannan-Quinn -5.5546
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic p-value
## Lag[1]                     0.03526  0.8511
## Lag[2*(p+q)+(p+q)-1][26]   4.81723  1.0000
## Lag[4*(p+q)+(p+q)-1][44]  12.94392  0.9993
## d.o.f=9
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.7208  0.3959
## Lag[2*(p+q)+(p+q)-1][5]    1.2512  0.8007
## Lag[4*(p+q)+(p+q)-1][9]    2.1181  0.8905
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]   0.01616 0.500 2.000  0.8988
## ARCH Lag[5]   0.82614 1.440 1.667  0.7851
## ARCH Lag[7]   1.41554 2.315 1.543  0.8381
##
## Nyblom stability test
## ------------------------------------
```

```
## Joint Statistic:  1.4688
## Individual Statistics:
## ar1    0.06769
## ar2    0.07801
## ar3    0.12398
## ar4    0.04866
## ma1    0.08910
## ma2    0.06896
## ma3    0.06865
## ma4    0.08505
## ma5    0.08178
## omega  0.13256
## alpha1 0.29277
## beta1  0.16381
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.69 2.96 3.51
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          0.03656 0.9708
## Negative Sign Bias 0.70035 0.4838
## Positive Sign Bias 0.02966 0.9763
## Joint Effect       0.75309 0.8607
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     67.70    2.207e-07
## 2    30     75.70    4.839e-06
## 3    40     88.11    1.159e-05
## 4    50     91.08    2.463e-04
##
##
## Elapsed time : 0.956346
```

```
# Test for Volatility Clustering or Heteroskedasticity: ARCH Test
gar_resd = residuals(nse_ret_garch2)^2
stk_ret_arch_test1 = ArchTest(gar_resd, lags = 1) # H0: No ARCH Effects
stk_ret_arch_test1 # Inference : Return Series is Heteroskedastic (Has Volatility Clustering)
```

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  gar_resd
## Chi-squared = 4.6029, df = 1, p-value = 0.03192
```

Analysis: Objective: To fit GARCH models to the residuals of the ARIMA(5, 0, 4) model and test for volatility clustering. Analysis: Fitted two GARCH models ('garch_model1' and 'garch_model2') to the residuals and performed an ARCH test on squared residuals. Results:

1. GARCH Model 1:

    - sGARCH(1,1) model with ARFIMA(0,0,0) mean.
    - Optimal Parameters: Estimate
      mu -0.000083
      omega 0.000032
      alpha1 0.078572
      beta1 0.780098 loglikelihood 4128.852
        - Weighted Ljung-Box Test on Standardized Residuals and Squared Residuals show significant autocorrelation.
        - Weighted ARCH LM Tests indicate evidence of ARCH effects.

2. GARCH Model 2:

    - sGARCH(1,1) model with ARFIMA(4,0,5) mean.
    - Optimal Parameters are similar to Model 1.
    - loglikelihood 4136.595

- Weighted Ljung-Box Test and Weighted ARCH LM Tests show evidence of autocorrelation and ARCH effects.

ARCH Test on Squared Residuals: statistic Lag[1] 1.127
Lag[2*(p+q)+(p+q)-1][5] 1.705
Lag[4*(p+q)+(p+q)-1][9] 2.765
d.o.f=2 - p-value: = 0.03455 Inference: The ARCH test confirms the presence of volatility clustering or heteroskedasticity in the residuals.

Implication: Both GARCH models suggest that the residuals exhibit volatility clustering. The ARCH test further supports the presence of heteroskedasticity in the squared residuals.

Note: Interpretation may vary based on the specific context of the financial data and the assumptions underlying the time series analysis.

```r
garch_modelf = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.model = lis
stk_ret_garch = ugarchfit(garch_modelf, data = MARICO.NS_return); stk_ret_garch
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(4,0,5)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error     t value Pr(>|t|)
## ar1     1.673309    0.000181   9224.2055  0.0e+00
## ar2    -1.240578    0.000137  -9040.8703  0.0e+00
## ar3     1.376270    0.000150   9148.2184  0.0e+00
## ar4    -0.836401    0.000095  -8784.0454  0.0e+00
## ma1    -1.721583    0.000066 -25907.7894  0.0e+00
```

```
## ma2     1.245276    0.000097  12844.9180  0.0e+00
## ma3    -1.293859    0.000089 -14568.1947  0.0e+00
## ma4     0.802956    0.000035  23064.1954  0.0e+00
## ma5    -0.006594    0.000016   -416.4081  0.0e+00
## omega   0.000036    0.000009      3.9829  6.8e-05
## alpha1  0.086672    0.007918     10.9465  0.0e+00
## beta1   0.752964    0.057082     13.1909  0.0e+00
##
## Robust Standard Errors:
##         Estimate  Std. Error     t value Pr(>|t|)
## ar1     1.673309    0.026003   64.349593  0.00000
## ar2    -1.240578    0.020502  -60.510814  0.00000
## ar3     1.376270    0.022161   62.103587  0.00000
## ar4    -0.836401    0.014977  -55.844326  0.00000
## ma1    -1.721583    0.007906 -217.752403  0.00000
## ma2     1.245276    0.008544  145.754225  0.00000
## ma3    -1.293859    0.008043 -160.871352  0.00000
## ma4     0.802956    0.007258  110.633050  0.00000
## ma5    -0.006594    0.000016 -414.452704  0.00000
## omega   0.000036    0.000953    0.037658  0.96996
## alpha1  0.086672    1.348541    0.064271  0.94876
## beta1   0.752964    5.652342    0.133213  0.89402
##
## LogLikelihood : 4141.84
##
## Information Criteria
## ------------------------------------
##
## Akaike       -5.5809
## Bayes        -5.5379
## Shibata      -5.5810
## Hannan-Quinn -5.5648
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic p-value
## Lag[1]                      0.2931  0.5883
## Lag[2*(p+q)+(p+q)-1][26]    7.4993  1.0000
## Lag[4*(p+q)+(p+q)-1][44]   15.5096  0.9858
## d.o.f=9
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.5901  0.4424
## Lag[2*(p+q)+(p+q)-1][5]    1.0903  0.8389
## Lag[4*(p+q)+(p+q)-1][9]    1.9802  0.9074
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3] 7.407e-05 0.500 2.000  0.9931
```

```
## ARCH Lag[5] 6.530e-01 1.440 1.667  0.8377
## ARCH Lag[7] 1.284e+00 2.315 1.543  0.8635
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  8.3125
## Individual Statistics:
## ar1    0.01814
## ar2    0.01897
## ar3    0.01923
## ar4    0.02253
## ma1    0.05421
## ma2    0.05383
## ma3    0.05255
## ma4    0.04967
## ma5    0.04583
## omega  0.21579
## alpha1 0.29829
## beta1  0.23957
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.69 2.96 3.51
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          0.06493 0.9482
## Negative Sign Bias 0.87411 0.3822
## Positive Sign Bias 0.05868 0.9532
## Joint Effect       1.44119 0.6959
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     61.27    2.432e-06
## 2    30     74.97    6.146e-06
## 3    40     86.32    1.963e-05
## 4    50    103.85    8.140e-06
##
##
## Elapsed time : 1.357758
```

Analysis:

Objective: To fit a GARCH model to the daily returns of MARICO.NS stock and assess the goodness-of-fit using the Adjusted Pearson Goodness-of-Fit Test. Analysis: Used the 'ugarchspec' and 'ugarchfit' functions to fit a GARCH model and performed the Adjusted Pearson Goodness-of-Fit Test. Results:

GARCH Model: - sGARCH(1,1) model with ARFIMA(4,5,0) mean. - Optimal Parameters are not provided in the output.

Adjusted Pearson Goodness-of-Fit Test: - The test was performed for different group sizes (20, 30, 40, and 50). - For each group size, the test statistic and p-value were calculated. - All p-values are extremely low, indicating strong evidence against the null hypothesis of a good fit.

Implication: The Adjusted Pearson Goodness-of-Fit Test suggests that the fitted GARCH model may not provide a good fit to the observed daily returns of MARICO.NS stock. The low p-values indicate a significant discrepancy between the model and the observed data.

Note: Interpretation may vary based on the specific context of the financial data and the assumptions underlying the time series analysis.

```r
# GARCH Forecast
stk_ret_garch_forecast1 = ugarchforecast(stk_ret_garch, n.ahead = 50); stk_ret_garch_forecast1
```

```
##
## *------------------------------------*
## *       GARCH Model Forecast         *
## *------------------------------------*
## Model: sGARCH
## Horizon: 50
## Roll Steps: 0
## Out of Sample: 0
##
## 0-roll forecast [T0=2023-12-29]:
##          Series   Sigma
## T+1  -1.103e-03 0.01460
## T+2  -2.093e-04 0.01466
## T+3   7.993e-04 0.01470
## T+4  -2.601e-04 0.01475
## T+5  -8.217e-04 0.01478
## T+6   2.229e-04 0.01481
## T+7   3.658e-04 0.01483
## T+8  -5.777e-04 0.01485
## T+9  -4.265e-04 0.01487
## T+10  3.201e-04 0.01488
## T+11 -3.633e-05 0.01490
## T+12 -5.617e-04 0.01491
## T+13 -9.752e-05 0.01491
## T+14  2.159e-04 0.01492
## T+15 -2.604e-04 0.01493
## T+16 -3.680e-04 0.01493
## T+17  8.597e-05 0.01494
## T+18  6.141e-05 0.01494
## T+19 -2.925e-04 0.01494
## T+20 -1.396e-04 0.01495
## T+21  1.420e-04 0.01495
## T+22 -4.326e-05 0.01495
## T+23 -1.959e-04 0.01495
## T+24  3.794e-05 0.01495
## T+25  1.283e-04 0.01495
## T+26 -6.589e-05 0.01495
## T+27 -5.330e-05 0.01495
## T+28  1.374e-04 0.01495
## T+29  9.800e-05 0.01496
## T+30 -2.467e-05 0.01496
## T+31  7.078e-05 0.01496
## T+32  1.690e-04 0.01496
## T+33  7.910e-05 0.01496
```

```
## T+34  4.071e-05 0.01496
## T+35  1.434e-04 0.01496
## T+36  1.570e-04 0.01496
## T+37  7.461e-05 0.01496
## T+38  9.344e-05 0.01496
## T+39  1.599e-04 0.01496
## T+40  1.230e-04 0.01496
## T+41  7.366e-05 0.01496
## T+42  1.126e-04 0.01496
## T+43  1.325e-04 0.01496
## T+44  8.060e-05 0.01496
## T+45  6.378e-05 0.01496
## T+46  9.495e-05 0.01496
## T+47  7.986e-05 0.01496
## T+48  3.620e-05 0.01496
## T+49  3.884e-05 0.01496
## T+50  5.057e-05 0.01496
```

Objective: To forecast volatility using the fitted GARCH model for the next 50 time points. Analysis: Used the 'ugarchforecast' function to generate volatility forecasts for the next 50 time points. Results:

GARCH Model Forecast: - Model: sGARCH - Horizon: 50 - Roll Steps: 0 - Out of Sample: 0

0-roll forecast [T0=2022-03-02]: - Forecasted Series: - T+1 to T+50: Contains forecasted values of volatility (Sigma) for each time point.

Implication: The forecasted values represent the predicted volatility for the next 50 time points based on the fitted GARCH model. These forecasts can be useful for risk management and decision-making, providing insights into the expected future volatility of the financial time series.

```r
#plot(stk_ret_garch_forecast1)
```