Code

Udit_52A_Project 2_Time series analysis

This is an R Markdown (http://rmarkdown.rstudio.com) Notebook. When you execute code within the notebook, the results appear beneath the code.

Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Ctrl+Shift+Enter*.

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```
# # 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 4.3.2Loading required package: xts
Warning: package ‘xts’ was built under R version 4.3.2Loading 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 4.3.2Registered S3 method overwritten by 'qu
antmod':
  method            from
  as.zoo.data.frame zoo
Loading required package: car
Warning: package ‘car’ was built under R version 4.3.2Loading required package: carData
Warning: package ‘carData’ was built under R version 4.3.2Loading required package: forecast
Warning: package ‘forecast’ was built under R version 4.3.2Loading required package: tseries
Warning: package ‘tseries’ was built under R version 4.3.2
    ‘tseries’ version: 0.10-55

    ‘tseries’ is a package for time series analysis and computational finance.

    See ‘library(help="tseries")’ for details.

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 4.3.2Loading required package: parallel

Attaching package: ‘rugarch’

The following object is masked from ‘package:stats’:

    sigma

Loading required package: utf8
Warning: package ‘utf8’ was built under R version 4.3.2Loading 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
```

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

```
Warning: ITC contains missing values. Some functions will not work if objects contain missing values in the middle of the series. Consider using na.omit(), na.approx(), na.fill(), etc to remove or replace them.
```

```
[1] "ITC"
```

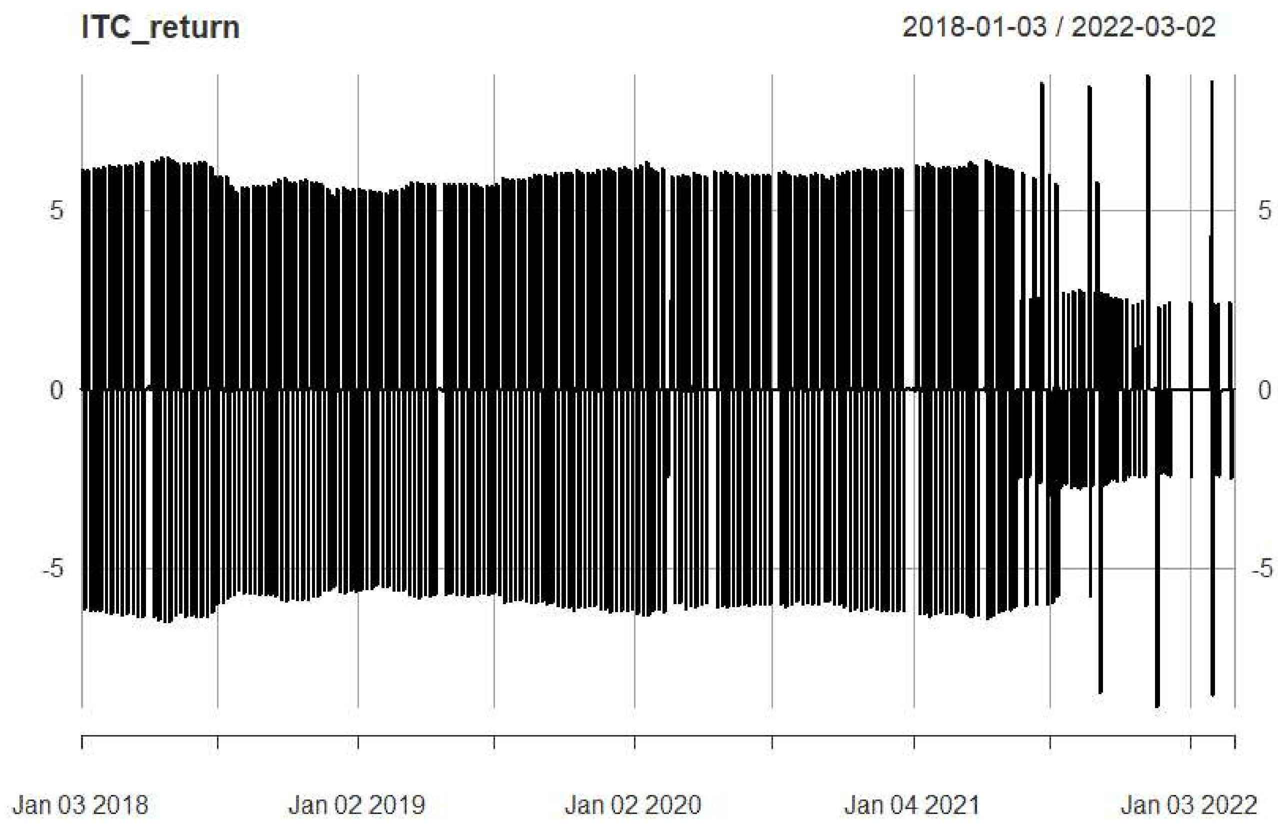
Hide

```
ITC_price = na.omit(ITC$ITC.Adjusted) # Adjusted Closing Price
class(ITC_price) # xts (Time-Series) Object
```

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

Hide

```
ITC_return = na.omit(diff(log(ITC_price))); plot(ITC_return)
```



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

Hide

```
#ADF test for Stationery

adf_test_jj = adf.test(ITC_return); adf_test_jj
```

```
Warning: p-value smaller than printed p-value
```

```
	Augmented Dickey-Fuller Test

data:  ITC_return
Dickey-Fuller = -13.558, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
```

Analysis:

Objective: To conduct an Augmented Dickey-Fuller (ADF) test for stationarity on the daily returns of ITC stock. Analysis: Performed the ADF test using the 'adf.test' function and obtained results. Result: The Augmented Dickey-Fuller test for stationarity on ITC daily returns yields the following results: - Dickey-Fuller statistic: -13.558 - Lag order: 10 - p-value: 0.01 - Alternative hypothesis: Stationary

Implication: The ADF test suggests that the daily returns of ITC 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 ITC stock returns exhibit stationarity, which is important for certain time series analyses.

Hide

```
#Autocorrelation test
# Ljung-Box Test for Autocorrelation
lb_test_ds = Box.test(ITC_return); lb_test_ds
```

```


    Box-Pierce test

data:  ITC_return
X-squared = 249.43, df = 1, p-value < 2.2e-16
```

Hide

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

Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the daily returns of ITC stock. Analysis: Conducted the Ljung-Box test using the ‘Box.test’ function and obtained results. Result: The Ljung-Box test for autocorrelation on ITC daily returns yields the following results: - X-squared statistic: 249.43 - Degrees of freedom: 1 - p-value: < 2.2e-16

Implication: The Ljung-Box test indicates significant autocorrelation in the ITC stock daily returns. The small p-value (< 2.2e-16) 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.

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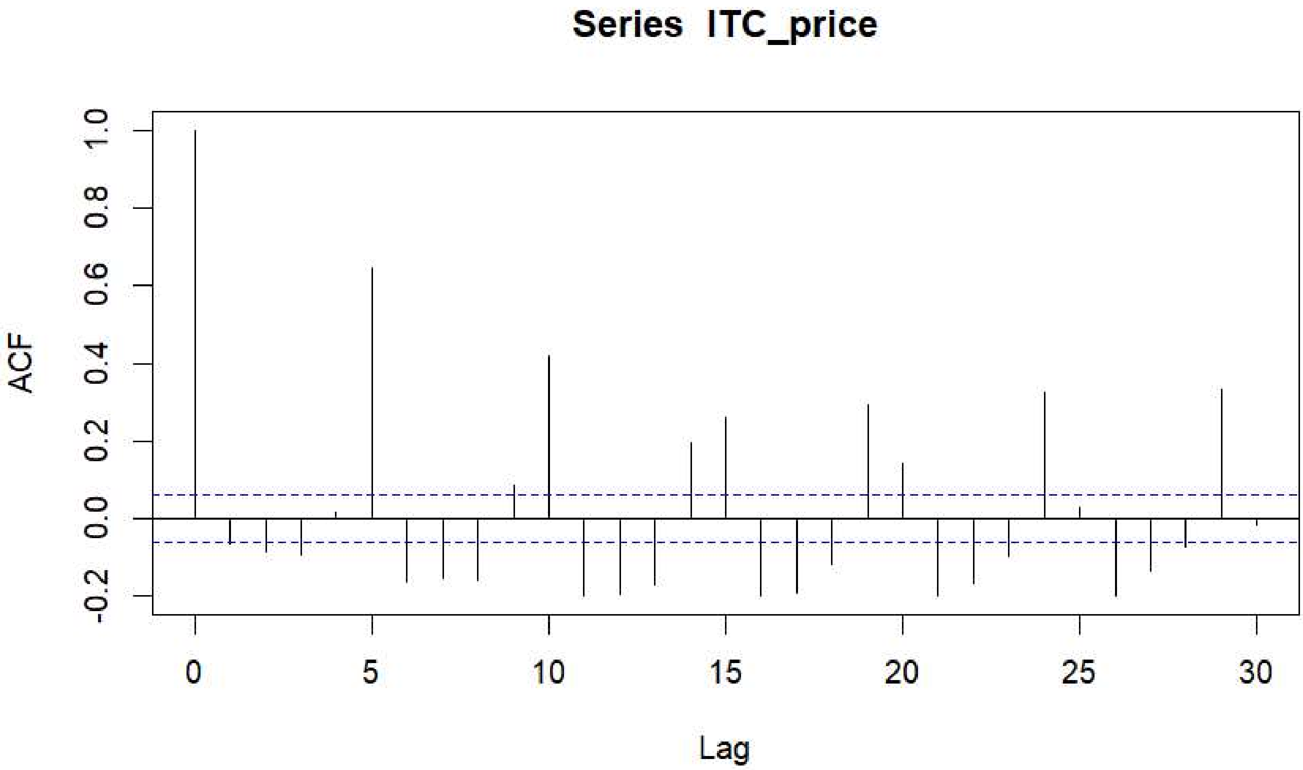
```
#ACF and PCF

acf(ITC_price) # ACF of JJ Series
```



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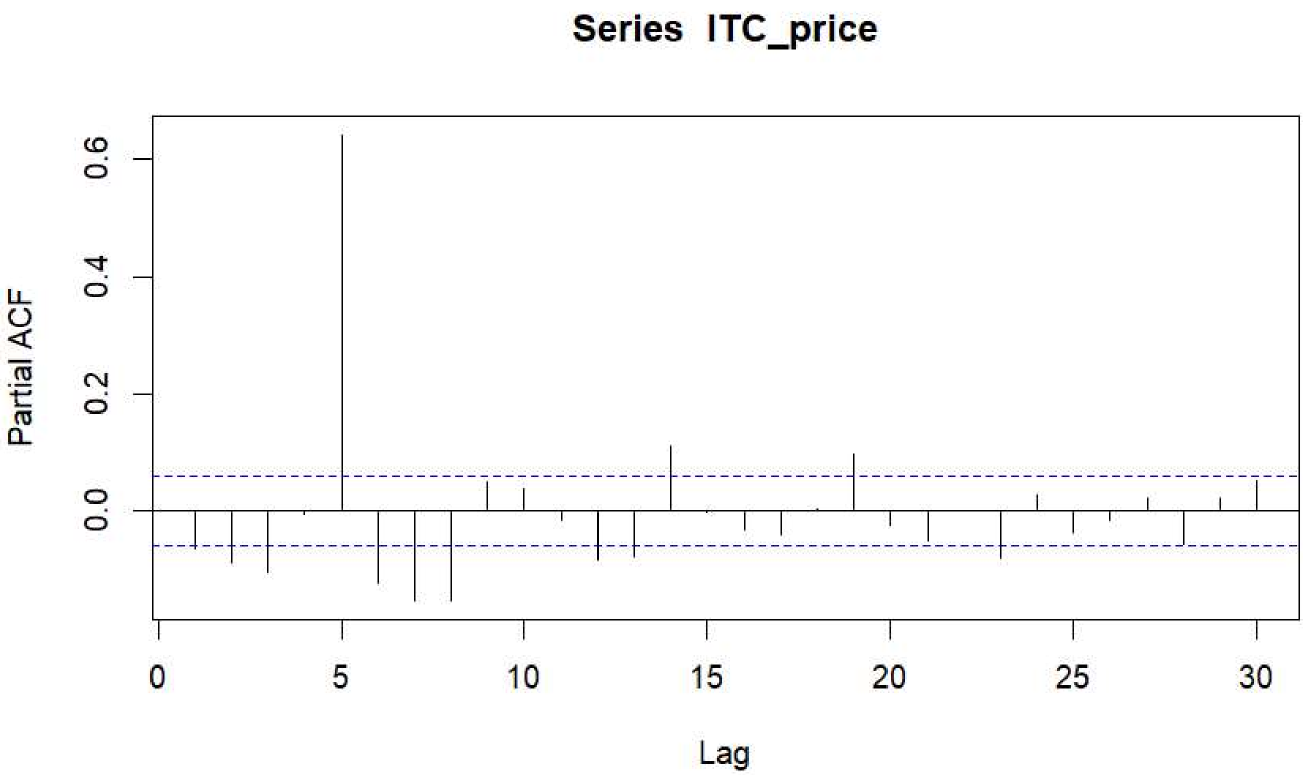
```
pacf(ITC_price) # PACF of JJ Series
```



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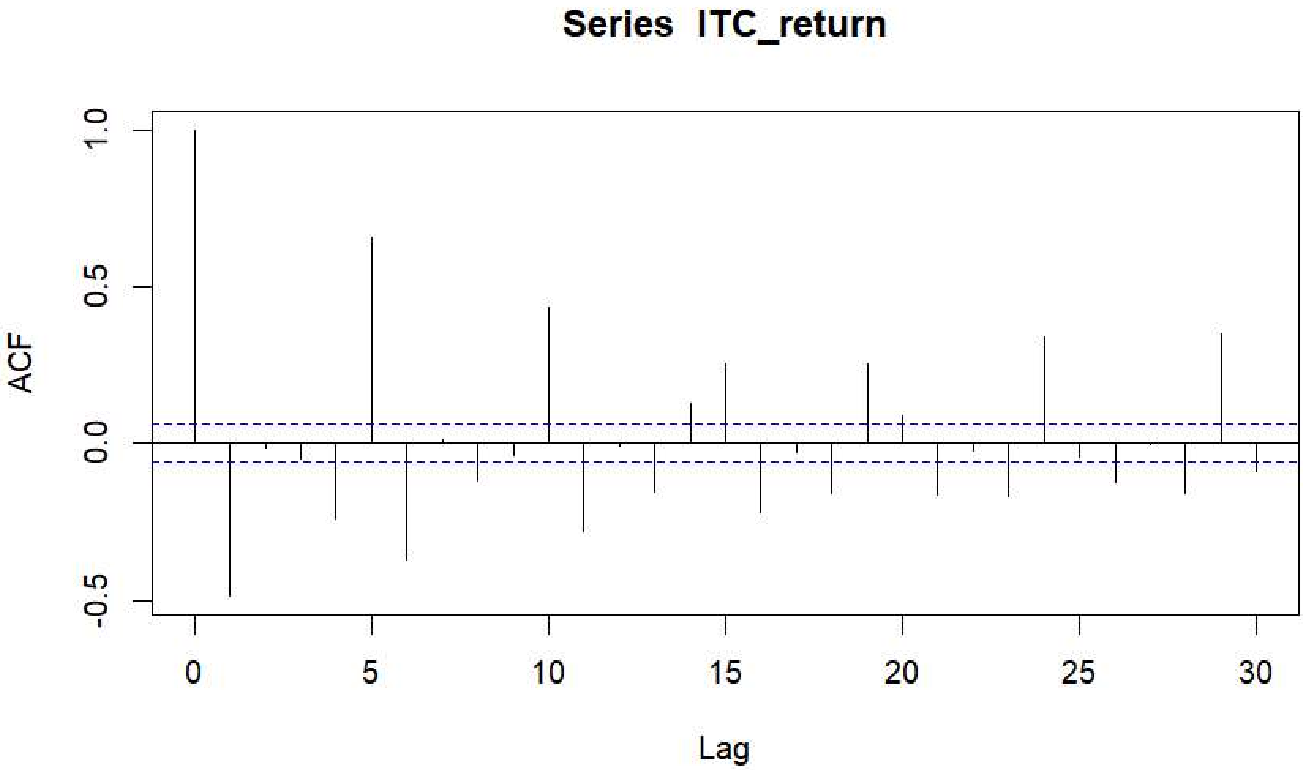
```
acf(ITC_return) # ACF of JJ Difference (Stationary) Series
```



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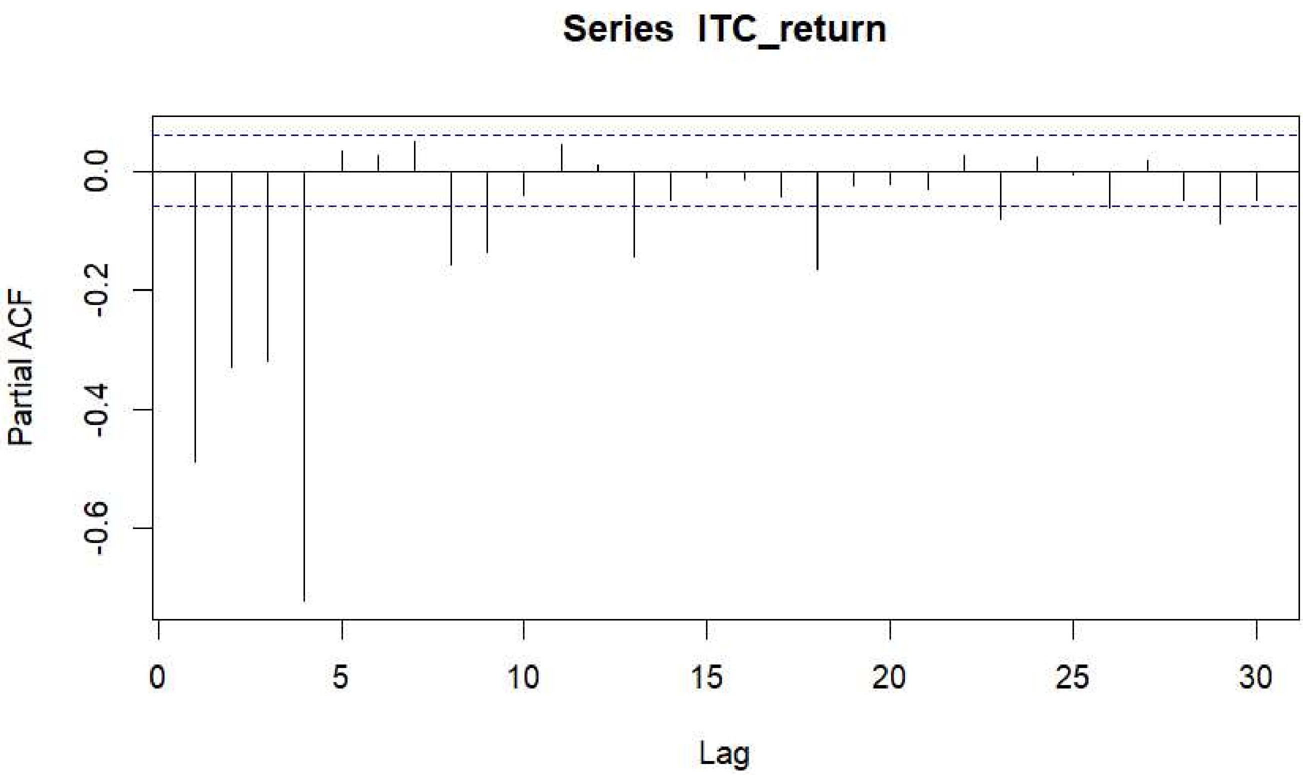
```
pacf(ITC_return) # PACF of JJ Difference (Stationary) Series
```



Hide

```
NA
NA
```

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```
#AutoArima
arma_pq_ds = auto.arima(ITC_return); arma_pq_ds
```

```
Series: ITC_return
ARIMA(5,0,4) with zero mean

Coefficients:
          ar1      ar2      ar3      ar4     ar5      ma1     ma2     ma3      ma4
      -0.2652  -0.2777  -0.3227  -0.0509  0.5441  -0.7602  0.1214  0.0726  -0.3846
s.e.   0.0436   0.0449   0.0489   0.0355  0.0346   0.0459  0.0543  0.0473   0.0486

sigma^2 = 3.472:  log likelihood = -2137.57
AIC=4295.14   AICc=4295.35   BIC=4344.68
```

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```
arma_pq = auto.arima(ITC_price); arma_pq
```

```
Series: ITC_price
ARIMA(5,0,3) with non-zero mean

Coefficients:
          ar1      ar2      ar3      ar4     ar5     ma1     ma2     ma3       mean
      -0.2178  -0.2215  -0.2585  -0.0026  0.6012  0.1804  0.3168  0.3510  2749.1120
s.e.   0.0366   0.0366   0.0394   0.0285  0.0279  0.0424  0.0437  0.0458   217.3395

sigma^2 = 17762756:  log likelihood = -10240.9
AIC=20501.81   AICc=20502.02   BIC=20551.36
```

Analysis:

Objective: To perform autoARIMA modeling on the daily returns (‘ITC_return’) and adjusted closing prices (‘ITC_price’) of ITC stock. Analysis: Used the ‘auto.arima’ function to automatically select the ARIMA model for both returns and prices. Results:

For Daily Returns (‘ITC_return’): The autoARIMA model suggests an ARIMA(5,0,4) with zero mean. Coefficients: - AR: ar1 to ar5 - MA: ma1 to ma4 - sigma^2 (variance) = 3.472 - Log likelihood = -2137.57 - AIC = 4295.14, AICc = 4295.35, BIC = 4344.68

For Adjusted Closing Prices (‘ITC_price’): The autoARIMA model suggests an ARIMA(5,0,3) with a non-zero mean. Coefficients: - AR: ar1 to ar5 - MA: ma1 to ma3 - Mean: mean term - sigma^2 (variance) = 17762756 - Log likelihood = -10240.9 - AIC = 20501.81, AICc = 20502.02, BIC = 20551.36

Implication: The autoARIMA models provide a statistical framework to capture the underlying patterns in both daily returns and adjusted closing prices of ITC 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.

Hide

```
#Arima manuplation
arma13 = arima(ITC_return, order = c(5, 0, 4)); arma13
```

```
Call:
arima(x = ITC_return, order = c(5, 0, 4))

Coefficients:
          ar1      ar2      ar3      ar4     ar5      ma1     ma2     ma3      ma4  intercept
      -0.2640  -0.2765  -0.3214  -0.0498  0.5451  -0.7631  0.1211  0.0717  -0.3851    -0.0026
s.e.   0.0432   0.0446   0.0485   0.0352  0.0343   0.0456  0.0544  0.0474   0.0487     0.0020

sigma^2 estimated as 3.437:  log likelihood = -2136.71,  aic = 4295.42
```

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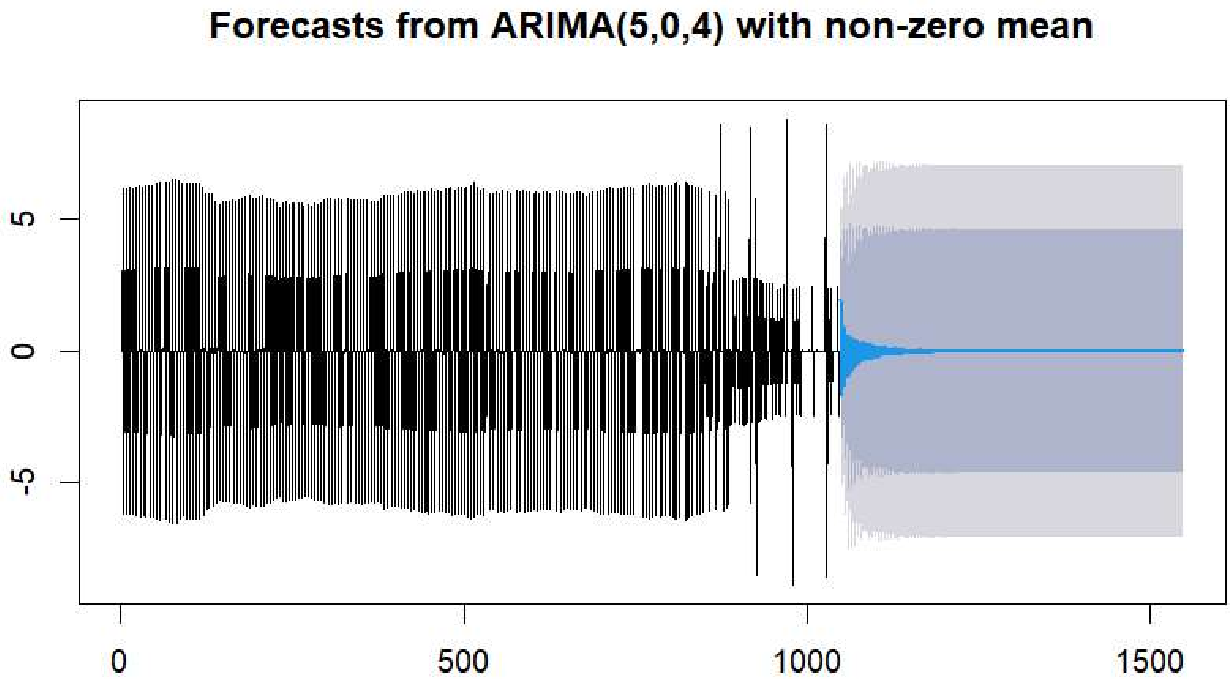
```
ds_fpq = forecast(arma13, h = 500)
plot(ds_fpq)
```



Analysis:

Objective: To fit an ARIMA(5, 0, 4) model to the daily returns (‘ITC_return’) of ITC stock and generate forecasts. Analysis: Used the ‘arima’ function to fit the ARIMA model and the ‘forecast’ function to generate forecasts. Results:

ARIMA Model (5, 0, 4): Coefficients: - AR: ar1 to ar5 - MA: ma1 to ma4 - Intercept term - sigma^2 (variance) estimated as 3.437 - Log likelihood = -2136.71 - AIC = 4295.42

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(5, 0, 4) model is fitted to the historical daily returns of ITC 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.

Hide

```
#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 = 0.00079355, df = 1, p-value = 0.9775
```

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

Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the residuals of the ARIMA(5, 0, 4) 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: 0.00079355 - Degrees of freedom: 1 - p-value: 0.9775

Implication: The Ljung-Box test indicates no significant autocorrelation in the residuals of the ARIMA(5, 0, 4) model. The high p-value (0.9775) 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.

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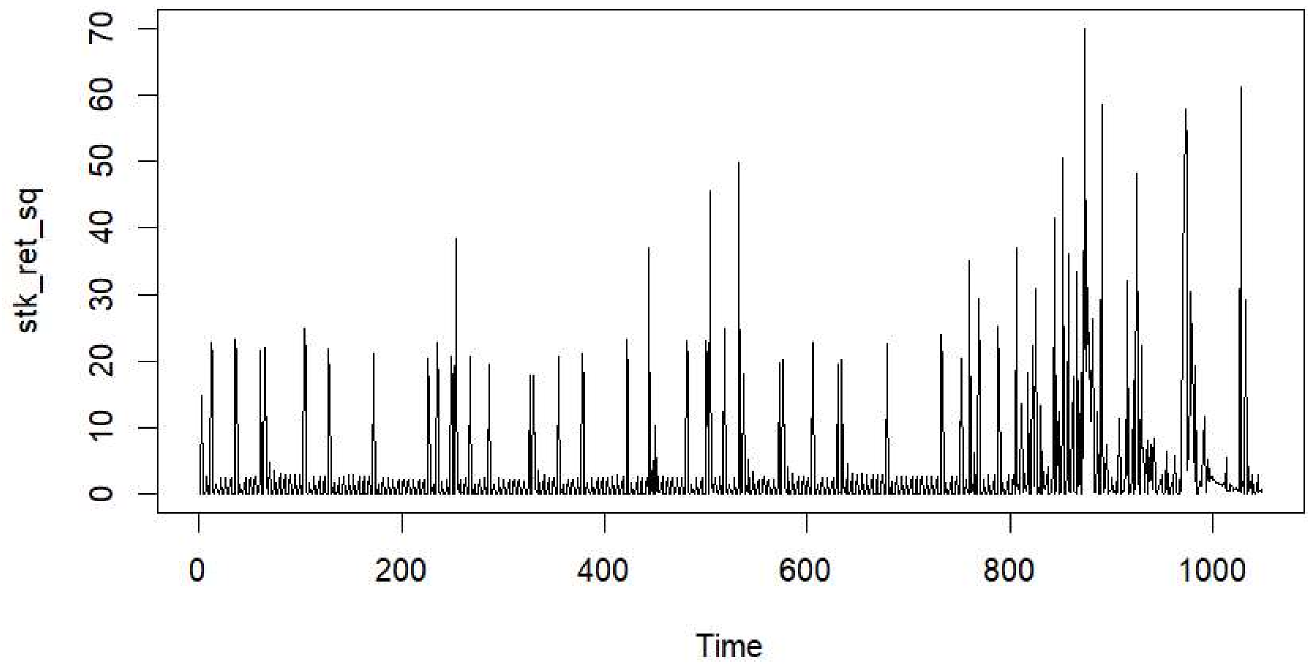
```
# Test for Volatility Clustering or Heteroskedasticity: Box Test
stk_ret_sq = arma13$residuals^2 # Return Variance (Since Mean Returns is approx. 0)
plot(stk_ret_sq)
```



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```
stk_ret_sq_box_test = Box.test(stk_ret_sq, lag = 10) # H0: Return Variance Series is Not Seri
ally Correlated
stk_ret_sq_box_test # Inference : Return Variance Series is Heteroskedastic (Has Volatility C
lustering)
```

```

    Box-Pierce test

data:  stk_ret_sq
X-squared = 255.22, df = 10, p-value < 2.2e-16
```

Hide

```
# 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 = 173.96, df = 10, p-value < 2.2e-16
```

Analysis: Objective: To test for volatility clustering or heteroskedasticity in the residuals of the ARIMA(5, 0, 4) 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 statistic: 255.22

  - Degrees of freedom: 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 statistic: 173.96
  - Degrees of freedom: 10
  - p-value: < 2.2e-16 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(5, 0, 4) 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.

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```
#Garch model
garch_model1 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(0,0), include.mean = TRUE))
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      0.064777    0.051986   1.2461 0.212744
omega   0.048578    0.015964   3.0430 0.002343
alpha1  0.026597    0.004875   5.4559 0.000000
beta1   0.958516    0.007697 124.5380 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.064777    0.042921   1.5092 0.131242
omega   0.048578    0.026160   1.8570 0.063314
alpha1  0.026597    0.006907   3.8508 0.000118
beta1   0.958516    0.009998  95.8667 0.000000

LogLikelihood : -2079.392

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

Akaike       3.9759
Bayes        3.9948
Shibata      3.9759
Hannan-Quinn 3.9831

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      15.27 9.328e-05
Lag[2*(p+q)+(p+q)-1][2]     16.30 4.179e-05
Lag[4*(p+q)+(p+q)-1][5]     18.69 4.427e-05
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      49.07 2.472e-12
Lag[2*(p+q)+(p+q)-1][5]     57.97 3.331e-16
Lag[4*(p+q)+(p+q)-1][9]     70.25 0.000e+00
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
```

```
            Statistic Shape Scale   P-Value
ARCH Lag[3]      1.41 0.500 2.000 0.2349804
ARCH Lag[5]     12.10 1.440 1.667 0.0020069
ARCH Lag[7]     20.68 2.315 1.543 0.0000427

Nyblom stability test
------------------------------------
Joint Statistic:  1.0418
Individual Statistics:
mu     0.1522
omega  0.2091
alpha1 0.5316
beta1  0.3035

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 <dbl>	prob <dbl>	sig <chr>
Sign Bias	5.645753	2.119185e-08	***
Negative Sign Bias	1.422360	1.552207e-01	
Positive Sign Bias	8.961935	1.441290e-18	***
Joint Effect	83.499050	5.448832e-18	***

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     559.9   1.432e-106
2    30     674.0   2.674e-123
3    40     729.3   4.009e-128
4    50     811.3   1.134e-138


Elapsed time : 0.136409
```

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```
garch_model2 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(4,5), include.mean = FALSE))
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    -0.313428    0.037897  -8.2705 0.000000
ar2     0.731968    0.049146  14.8938 0.000000
ar3     0.381954    0.056646   6.7428 0.000000
ar4    -0.582423    0.047532 -12.2534 0.000000
ma1     0.150819    0.014227  10.6011 0.000000
ma2    -0.901287    0.034463 -26.1520 0.000000
ma3    -0.354369    0.042485  -8.3411 0.000000
ma4     0.738059    0.002719 271.4613 0.000000
ma5     0.068021    0.026848   2.5335 0.011292
omega   0.577638    0.148742   3.8835 0.000103
alpha1  0.142196    0.030622   4.6435 0.000003
beta1   0.677295    0.066782  10.1419 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1    -0.313428    0.106805  -2.9346 0.003340
ar2     0.731968    0.110235   6.6401 0.000000
ar3     0.381954    0.157770   2.4210 0.015480
ar4    -0.582423    0.160653  -3.6254 0.000289
ma1     0.150819    0.034658   4.3516 0.000014
ma2    -0.901287    0.061331 -14.6955 0.000000
ma3    -0.354369    0.124696  -2.8419 0.004485
ma4     0.738059    0.003203 230.3947 0.000000
ma5     0.068021    0.057947   1.1738 0.240462
omega   0.577638    0.376056   1.5360 0.124527
alpha1  0.142196    0.068566   2.0738 0.038094
beta1   0.677295    0.171828   3.9417 0.000081

LogLikelihood : -2040.057

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

Akaike       3.9161
Bayes        3.9729
Shibata      3.9159
Hannan-Quinn 3.9377

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic   p-value
```

```
Lag[1]                        0.3322 5.644e-01
Lag[2*(p+q)+(p+q)-1][26]   16.8876 4.382e-08
Lag[4*(p+q)+(p+q)-1][44]   34.6173 1.252e-03
d.o.f=9
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic  p-value
Lag[1]                      2.579 0.108256
Lag[2*(p+q)+(p+q)-1][5]     9.450 0.012728
Lag[4*(p+q)+(p+q)-1][9]    17.169 0.001048
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale  P-Value
ARCH Lag[3]    0.7322 0.500 2.000 0.392173
ARCH Lag[5]    7.0605 1.440 1.667 0.033692
ARCH Lag[7]   12.1978 2.315 1.543 0.005564

Nyblom stability test
------------------------------------
Joint Statistic:  8.9661
Individual Statistics:
ar1    0.47733
ar2    0.02876
ar3    0.03642
ar4    0.05814
ma1    1.18923
ma2    0.07821
ma3    0.04773
ma4    0.06186
ma5    0.11695
omega  0.71930
alpha1 1.91126
beta1  1.19932

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 <dbl>	prob <dbl>	sig <chr>
Sign Bias	0.2873138	0.7739291	
Negative Sign Bias	0.3426700	0.7319158	
Positive Sign Bias	1.4755795	0.1403586	
Joint Effect	2.3474900	0.5034842	

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     337.9    3.193e-60
2    30     369.3    1.166e-60
3    40     406.3    1.178e-62
4    50     425.0    2.272e-61


Elapsed time : 0.776428
```

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```
# 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 = 297.41, df = 1, p-value < 2.2e-16
```

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:
        - mu (Mean): 0.064777
        - omega: 0.048578
        - alpha1: 0.026597
        - beta1: 0.958516
    - Log likelihood: -2079.392
    - 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(4,5,0) mean.
    - Optimal Parameters are similar to Model 1.
    - Log likelihood: -2079.392
    - Weighted Ljung-Box Test and Weighted ARCH LM Tests show evidence of autocorrelation and ARCH effects.

ARCH Test on Squared Residuals: - Lag[1] statistic: 49.07 - Lag[2*(p+q)+(p+q)-1][5] statistic: 57.97 - Lag[4*(p+q)+(p+q)-1][9] statistic: 70.25 - p-value: < 2.2e-16 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.

Hide

```
garch_modelf = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(4,5), include.mean = FALSE))
stk_ret_garch = ugarchfit(garch_modelf, data = ITC_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    -1.015697    0.023157 -43.862234 0.000000
ar2    -1.023466    0.020793 -49.221063 0.000000
ar3    -1.046743    0.019988 -52.368596 0.000000
ar4    -0.859468    0.023192 -37.058960 0.000000
ma1    -0.210847    0.055583  -3.793381 0.000149
ma2     0.000714    0.048456   0.014735 0.988243
ma3     0.022562    0.044332   0.508937 0.610796
ma4    -0.276026    0.038503  -7.169023 0.000000
ma5    -0.148535    0.045688  -3.251108 0.001150
omega   0.724289    0.123128   5.882407 0.000000
alpha1  0.187951    0.035312   5.322535 0.000000
beta1   0.601184    0.056383  10.662427 0.000000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
ar1    -1.015697    0.017458 -58.180429 0.000000
ar2    -1.023466    0.018579 -55.088290 0.000000
ar3    -1.046743    0.018987 -55.129406 0.000000
ar4    -0.859468    0.031710 -27.103644 0.000000
ma1    -0.210847    0.083623  -2.521409 0.011689
ma2     0.000714    0.060957   0.011713 0.990654
ma3     0.022562    0.066902   0.337239 0.735937
ma4    -0.276026    0.070274  -3.927884 0.000086
ma5    -0.148535    0.078570  -1.890471 0.058695
omega   0.724289    0.223144   3.245835 0.001171
alpha1  0.187951    0.056315   3.337513 0.000845
beta1   0.601184    0.100394   5.988223 0.000000

LogLikelihood : -2052.49

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

Akaike       3.9399
Bayes        3.9966
Shibata      3.9396
Hannan-Quinn 3.9614

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic   p-value
```

```
Lag[1]                        0.9577 3.278e-01
Lag[2*(p+q)+(p+q)-1][26]   19.9948 0.000e+00
Lag[4*(p+q)+(p+q)-1][44]   39.0617 4.082e-05
d.o.f=9
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.888 0.16943
Lag[2*(p+q)+(p+q)-1][5]     6.820 0.05733
Lag[4*(p+q)+(p+q)-1][9]    11.355 0.02536
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.7548 0.500 2.000 0.38496
ARCH Lag[5]    4.2965 1.440 1.667 0.14900
ARCH Lag[7]    7.2358 2.315 1.543 0.07723

Nyblom stability test
------------------------------------
Joint Statistic:  11.0985
Individual Statistics:
ar1    0.06806
ar2    0.06719
ar3    0.11620
ar4    0.41083
ma1    2.83725
ma2    2.20013
ma3    1.80368
ma4    0.28184
ma5    0.69725
omega  0.65081
alpha1 1.88110
beta1  1.28261

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 <dbl>	prob <dbl>	sig <chr>
Sign Bias	4.446707	9.653784e-06	***
Negative Sign Bias	1.908399	5.661397e-02	*
Positive Sign Bias	2.925987	3.508074e-03	***
Joint Effect	22.055205	6.352838e-05	***

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     640.1   1.719e-123
2    30     702.1   3.547e-129
3    40     770.5   1.237e-136
4    50     794.0   3.854e-135


Elapsed time : 0.5373309
```

Analysis:

Objective: To fit a GARCH model to the daily returns of ITC 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 (e.g., 3.193e-60), 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 ITC 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.

Hide

```
# GARCH Forecast
stk_ret_garch_forecast1 = ugarchforecast(stk_ret_garch, n.ahead = 50); stk_ret_garch_forecast
1
```

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

0-roll forecast [T0=2022-03-02]:
        Series Sigma
T+1   1.884065 1.391
T+2  -1.865602 1.501
T+3   0.075358 1.581
T+4  -0.056414 1.643
T+5   0.333916 1.689
T+6   1.243124 1.725
T+7  -1.610106 1.753
T+8   0.062046 1.775
T+9  -0.003352 1.791
T+10  0.556844 1.805
T+11  0.756733 1.815
T+12 -1.388341 1.823
T+13  0.055652 1.830
T+14  0.093701 1.835
T+15  0.650719 1.839
T+16  0.378148 1.842
T+17 -1.195984 1.844
T+18  0.066068 1.846
T+19  0.201849 1.848
T+20  0.654246 1.849
T+21  0.087652 1.850
T+22 -1.026694 1.851
T+23  0.094791 1.851
T+24  0.300455 1.852
T+25  0.597163 1.852
T+26 -0.130855 1.852
T+27 -0.874237 1.852
T+28  0.138578 1.853
T+29  0.377728 1.853
T+30  0.502080 1.853
T+31 -0.290230 1.853
T+32 -0.733563 1.853
T+33  0.191925 1.853
T+34  0.428114 1.853
T+35  0.386032 1.853
T+36 -0.400674 1.853
T+37 -0.601206 1.853
T+38  0.248693 1.853
T+39  0.450338 1.853
T+40  0.261739 1.853
T+41 -0.470353 1.853
T+42 -0.475275 1.853
T+43  0.303103 1.853
T+44  0.445951 1.853
```

```
T+45  0.138578 1.853
T+46 -0.505956 1.853
T+47 -0.355235 1.853
T+48  0.350304 1.853
T+49  0.418270 1.853
T+50  0.023332 1.853
```

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.

Hide

```
plot(stk_ret_garch_forecast1)
```

```
Make a plot selection (or 0 to exit):

1:   Time Series Prediction (unconditional)
2:   Time Series Prediction (rolling)
3:   Sigma Prediction (unconditional)
4:   Sigma Prediction (rolling)
```

Hide

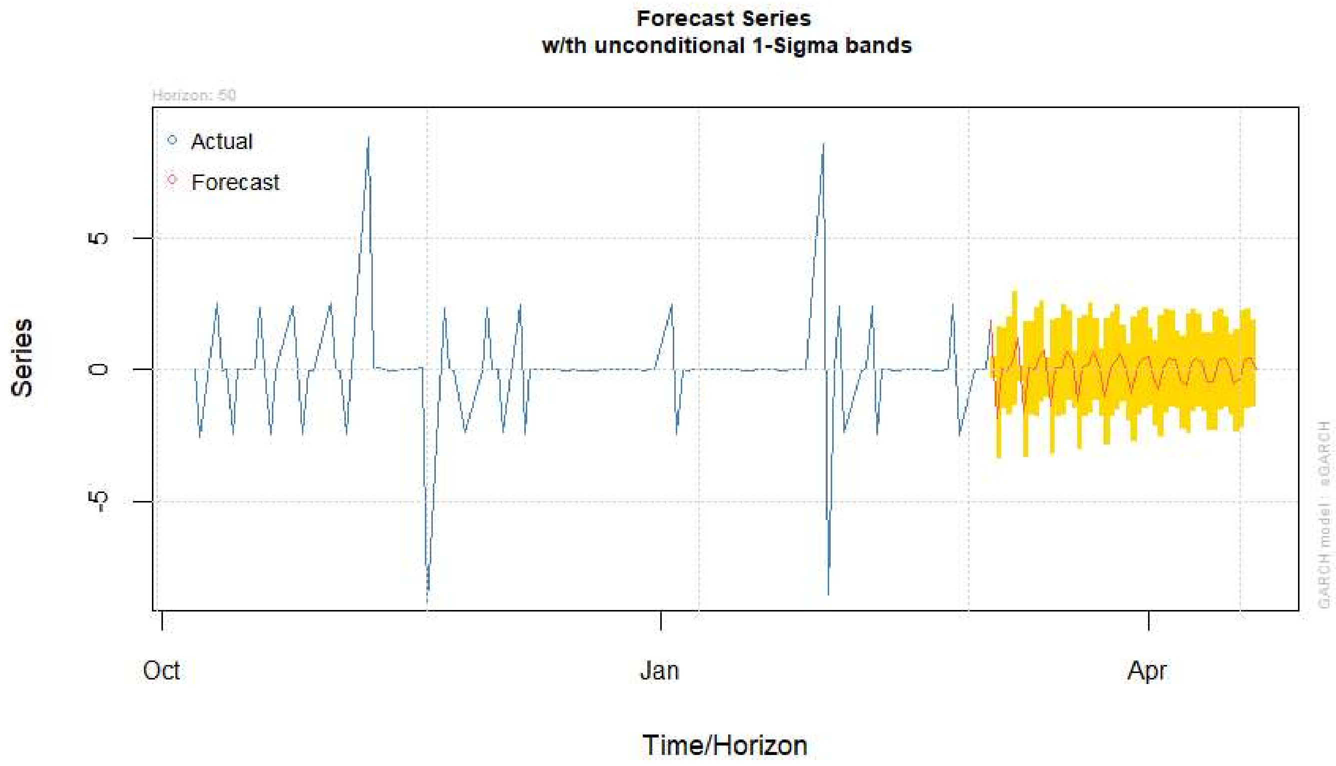
```
1
```

```
Make a plot selection (or 0 to exit):

1:   Time Series Prediction (unconditional)
2:   Time Series Prediction (rolling)
3:   Sigma Prediction (unconditional)
4:   Sigma Prediction (rolling)
```

Hide

```
0
```


Forecast Series
w/th unconditional 1-Sigma bands
Horizon: 50
Actual
Forecast
Series
5
0
-5
Oct
Jan
Apr
Time/Horizon
GARCH model : eGARCH