Anushka Nagpure_5A_Project 2_Time series analysis

Code

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*.

Hide

```
# # Required Packages
```

```
Warning message:
package ‘rugarch’ was built under R version 4.3.2
```

Hide

```
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: utf8
Warning: package ‘utf8’ was built under R version 4.3.2Loading required package: ggplot2
Warning: package ‘ggplot2’ was built under R version 4.3.2Learn more about the underlying the
ory at
https://ggplot2-book.org/
```

```
[[1]]
[1] TRUE

[[2]]
[1] TRUE

[[3]]
[1] TRUE

[[4]]
[1] TRUE

[[5]]
[1] TRUE

[[6]]
[1] TRUE

[[7]]
[1] TRUE

[[8]]
[1] TRUE
```

Hide

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

```
[1] "ICICIBANK.NS"
```

Hide

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

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

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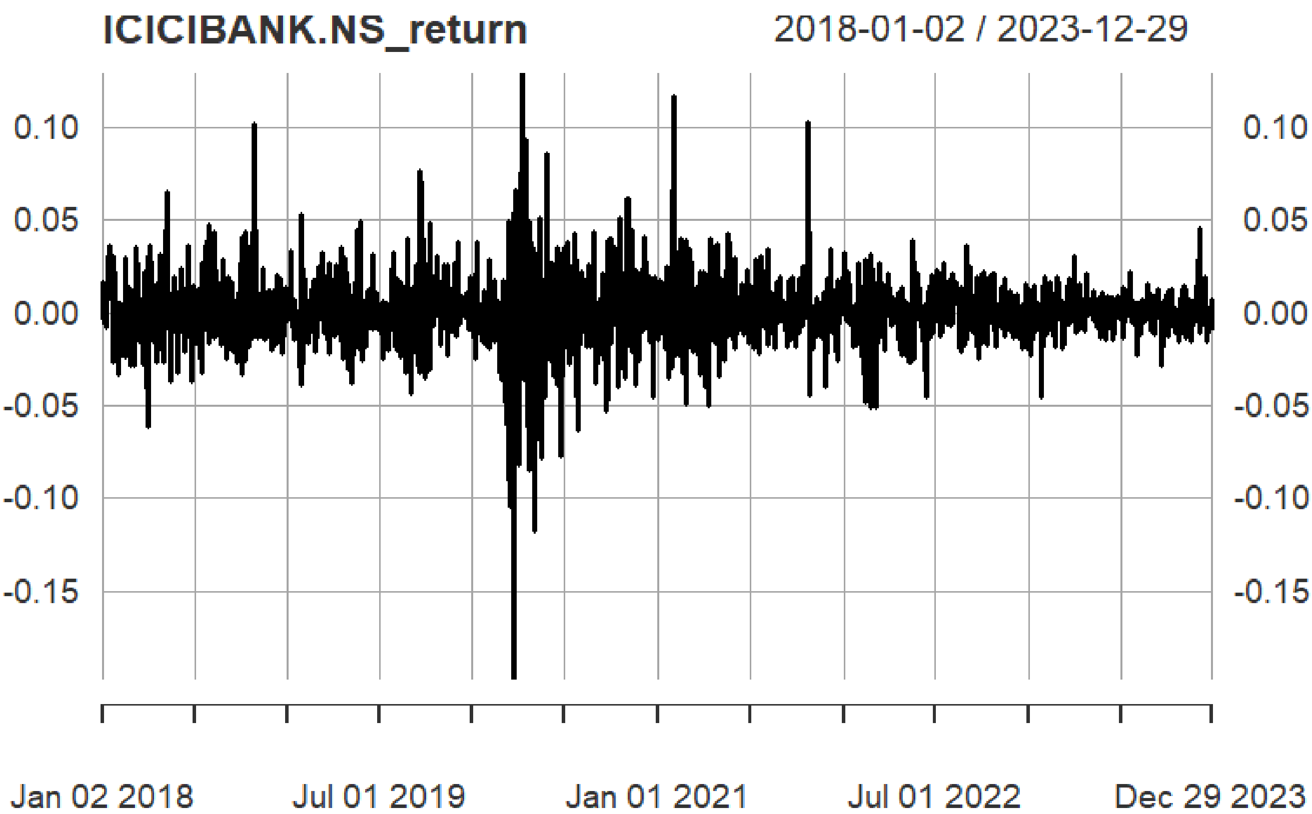
```
ICICIBANK.NS_return = na.omit(diff(log(ICICIBANK.NS_price)));
plot(ICICIBANK.NS_price)
```

Hide

```
plot(ICICIBANK.NS_return)
```



Analysis: Objective: To analyze the daily returns of ICICI BANK stock from 2018-01-01 to 2023-12-31. Analysis: Extracted the adjusted closing prices of ICICI BANK stock, calculated daily returns, and visualized them. Result: The 'ICICIBANK.NS' plot displays the daily returns of ICICI BANK stock over the specified period.

Implication: The plot indicates the volatility and direction of daily returns for ICICI BANK stock during the given time frame. Observations from the plot can help investors understand the historical performance and risk associated with ITC stock.

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```
#ADF test for Stationery

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

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

```

    Augmented Dickey-Fuller Test

data:  ICICIBANK.NS_return
Dickey-Fuller = -10.345, 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 ICICI BANK stock. Analysis: Performed the ADF test using the ‘adf.test’ function and obtained results. Result: The Augmented Dickey-Fuller test for stationarity on ICICI BANK daily returns yields the following results: - Dickey-Fuller statistic: -10.345 - Lag order: 11 - p-value: 0.01 - Alternative hypothesis: Stationary

Implication: The ADF test suggests that the daily returns of ICICI BANK 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 ICICI BANK 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(ICICIBANK.NS_return); lb_test_ds
```

```

    Box-Pierce test

data:  ICICIBANK.NS_return
X-squared = 1.9756, df = 1, p-value = 0.1599
```

Hide

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

Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the daily returns of ICICI BANK stock. Analysis: Conducted the Ljung-Box test using the ‘Box.test’ function and obtained results. Result: The Ljung-Box test for autocorrelation on ICICI BANK daily returns yields the following results: - X-squared statistic: 1.9756 - Degrees of freedom: 1 - p-value: 0.1599

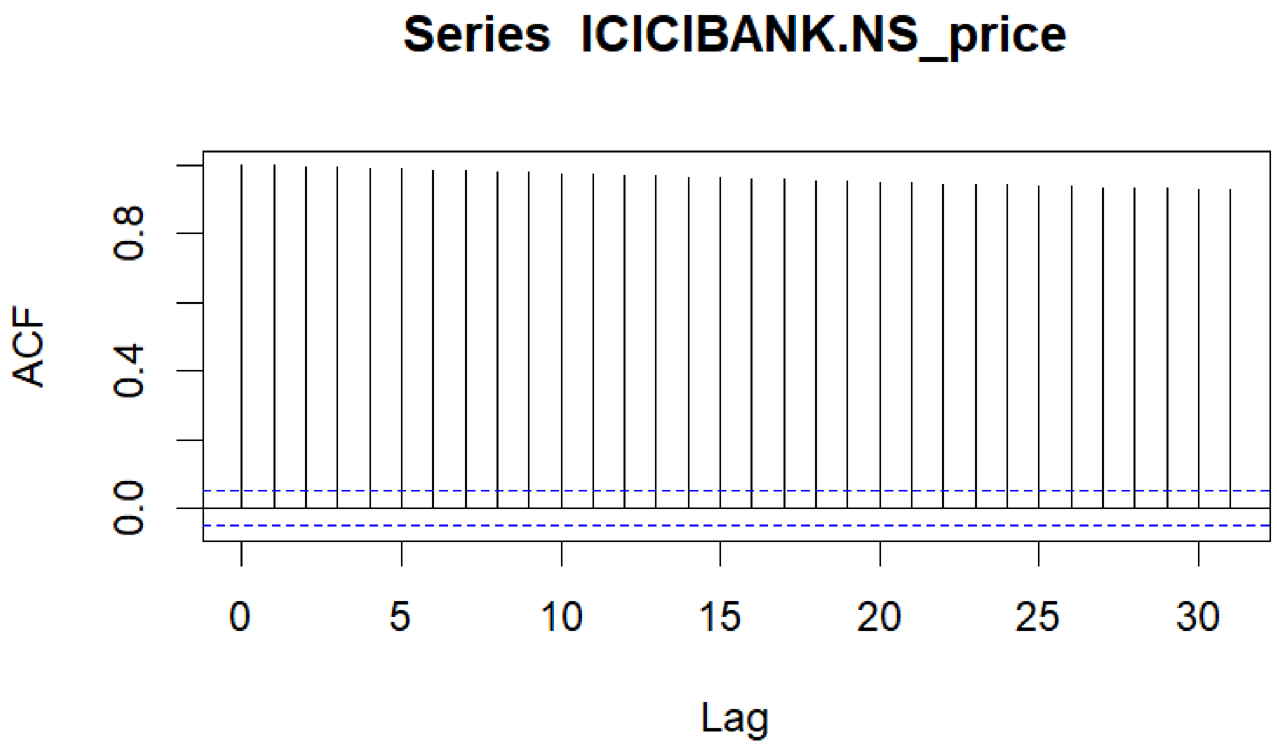
Implication: The Ljung-Box test indicates significant autocorrelation in the ICICI BANK stock daily returns. The p-value (0.1599) suggests that there is not enough evidence to reject the null hypothesis of no autocorrelation. In other words, based on this test alone, it appears that there may not be significant autocorrelation present.

Action: Given that there is no presence of autocorrelation, it may be advisable to not to consider an autoARIMA model for time series forecasting.

Hide

```
#ACF and PCF

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



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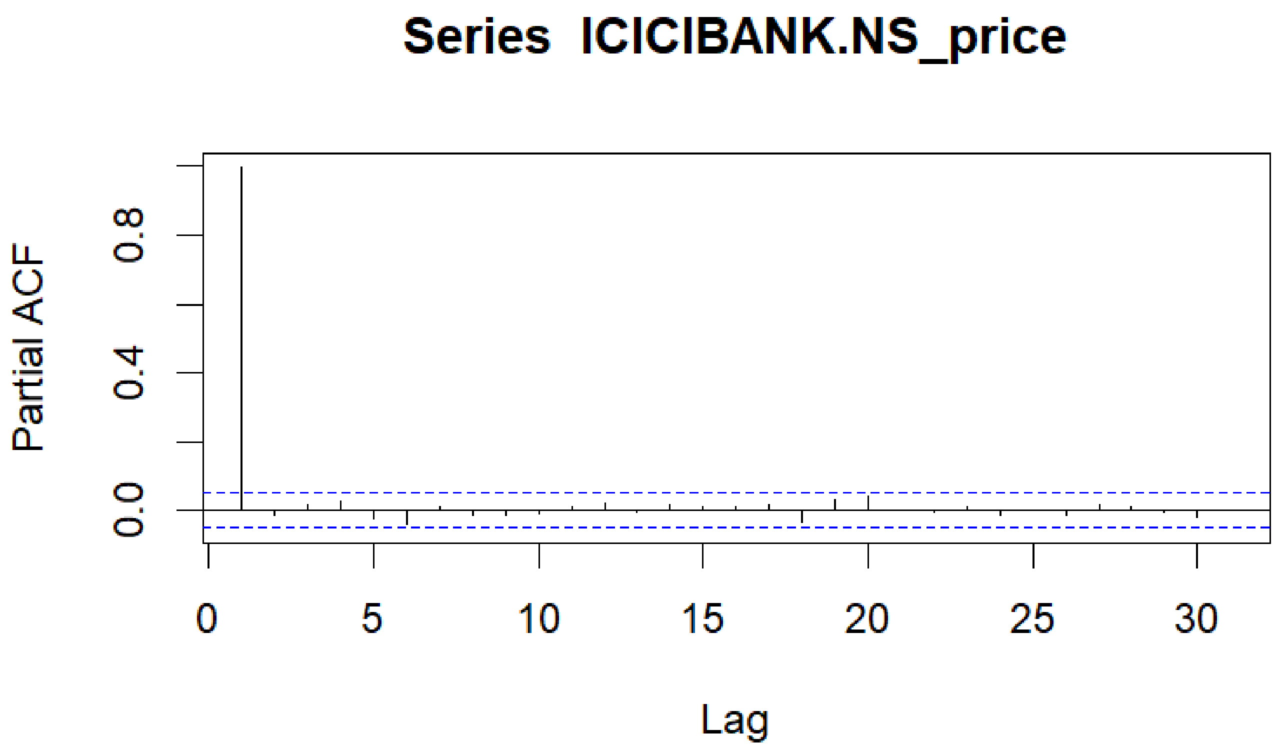
```
pacf(ICICIBANK.NS_price) # PACF of JJ Series
```



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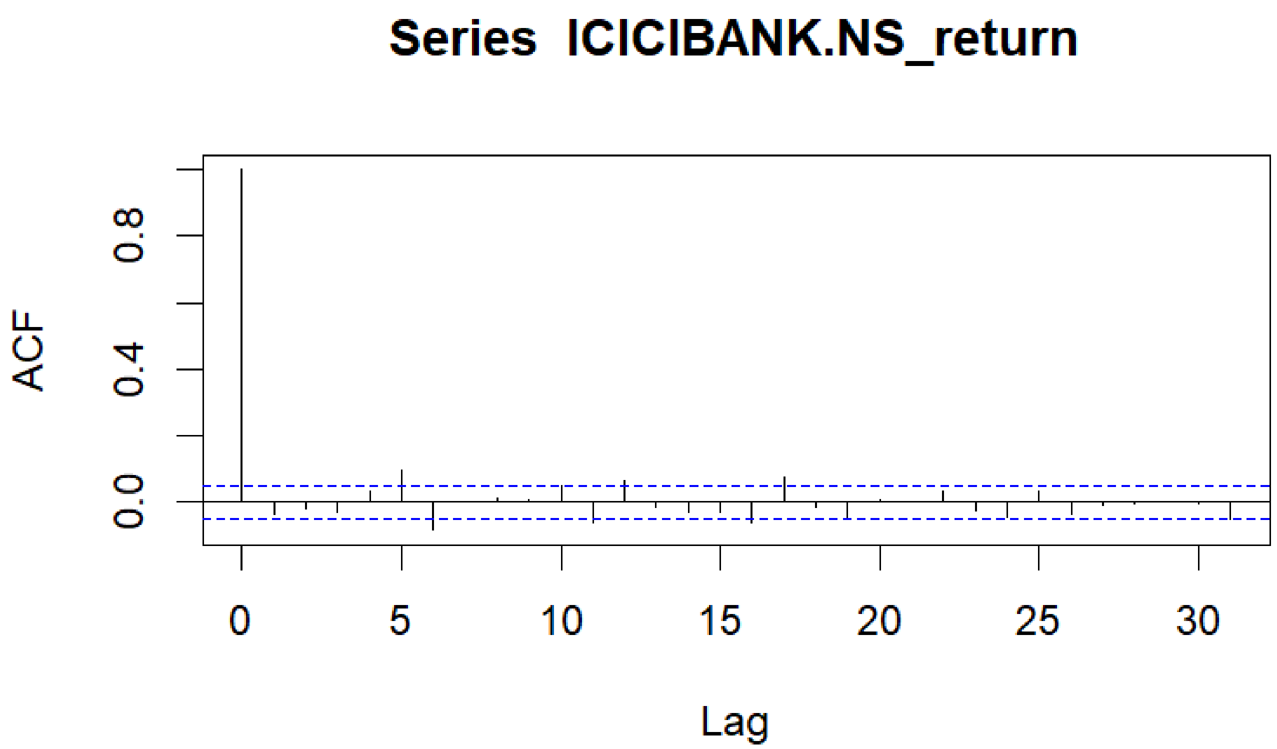
```
acf(ICICIBANK.NS_return) # ACF of JJ Difference (Stationary) Series
```



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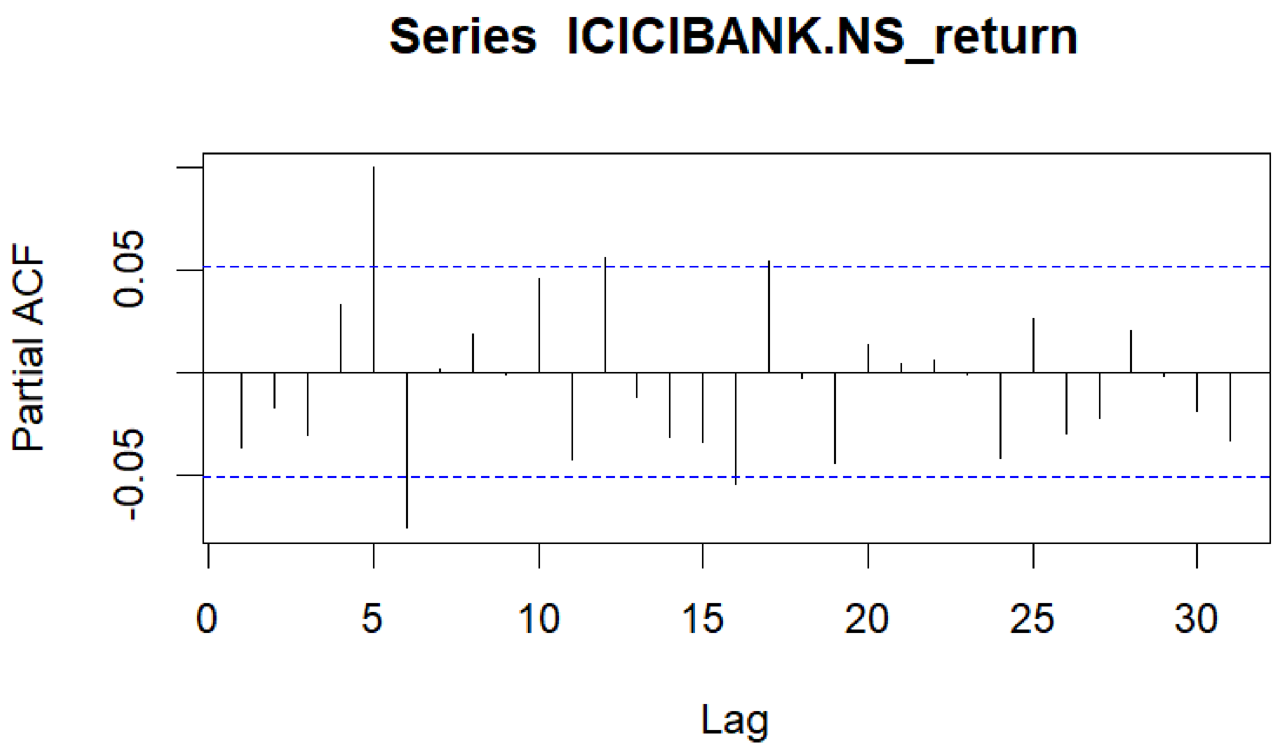
```
pacf(ICICIBANK.NS_return) # PACF of JJ Difference (Stationary) Series
```



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```
NA
NA
```

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

```
Series: ICICIBANK.NS_return
ARIMA(3,0,2) with non-zero mean

Coefficients:
          ar1      ar2      ar3      ma1     ma2   mean
      -0.0095  -0.8631  -0.0789  -0.0295  0.8354  8e-04
s.e.   0.0999   0.0550   0.0287   0.0979  0.0617  5e-04

sigma^2 = 0.0004207:  log likelihood = 3655.33
AIC=-7296.66   AICc=-7296.58   BIC=-7259.56
```

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```
arma_pq = auto.arima(ICICIBANK.NS_price); arma_pq
```

```
Series: ICICIBANK.NS_price
ARIMA(2,1,3) with drift

Coefficients:
          ar1      ar2     ma1     ma2      ma3   drift
      -0.4150  -0.7048  0.4275  0.7008  -0.0671  0.4720
s.e.   0.1306   0.1775  0.1322  0.1856   0.0345  0.2516

sigma^2 = 99.47:  log likelihood = -5500.98
AIC=11015.97   AICc=11016.04   BIC=11053.06
```

Note: Although there is no autocorrelation in ICICI BANK returns data; for academic understanding purpose, I have executed the code. Analysis:

Objective: To perform autoARIMA modeling on the daily returns (‘ICICIBANK_return’) and adjusted closing prices (‘ICICIBANK_price’) of ICICI BANK stock.

Analysis: Used the ‘auto.arima’ function to automatically select the ARIMA model for both returns and prices. Results:

For Daily Returns (‘ICICIBANK.NS_return’): The autoARIMA model suggests an ARIMA(3,0,2) with zero mean. Coefficients: - AR: ar1 to ar3 - MA: ma1 to ma2 - sigma^2 (variance) = 0.0004207 - Log likelihood = 3655.33 - AIC=-7296.65 AICc=-7296.58 BIC=-7259.56

For Adjusted Closing Prices (‘ICICIBANK.NS_price’): The autoARIMA model suggests an ARIMA(2,1,3) with a non-zero mean. Coefficients: - AR: ar1 to ar2 - MA: ma1 to ma3 - Mean: mean term - sigma^2 (variance) = 99.47 - Log likelihood = -5500.98 - AIC=11015.97 AICc=11016.04 BIC=11053.06

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

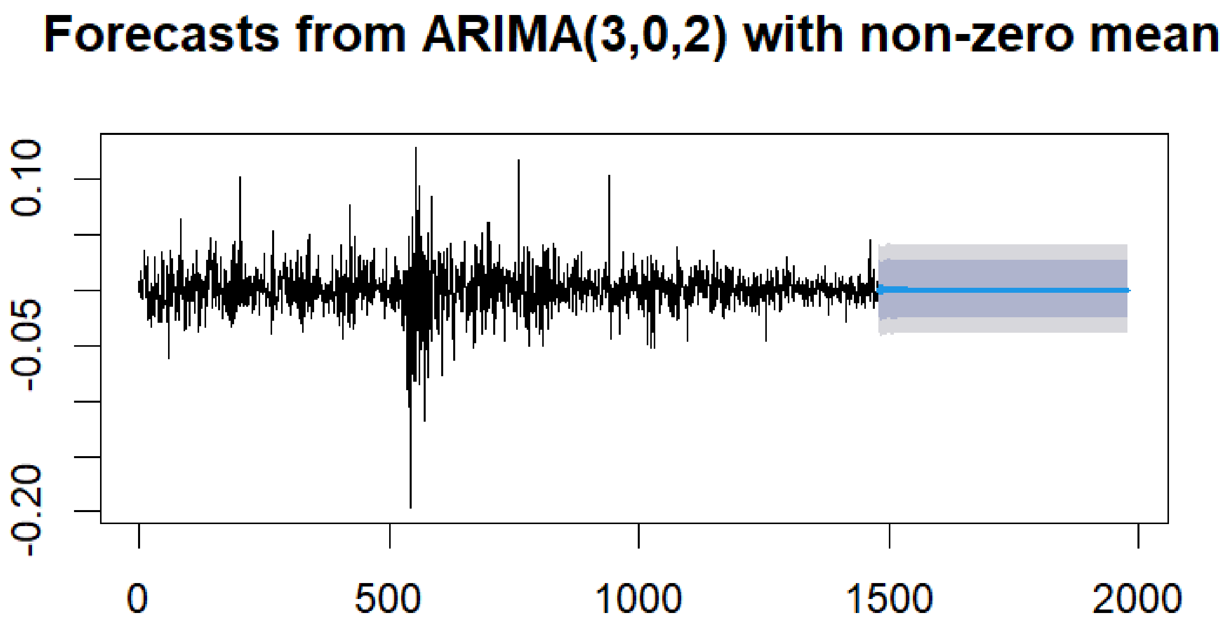
Hide

```
#Arima manuplation
arma13 = arima(ICICIBANK.NS_return, order = c(3, 0, 2)); arma13
```

```


Call:
arima(x = ICICIBANK.NS_return, order = c(3, 0, 2))

Coefficients:
          ar1      ar2      ar3      ma1     ma2  intercept
      -0.0095  -0.8631  -0.0789  -0.0295  0.8354      8e-04
s.e.   0.0999   0.0550   0.0287   0.0979  0.0617      5e-04

sigma^2 estimated as 0.000419:  log likelihood = 3655.33,  aic = -7296.66
```

Hide

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



Analysis:

Objective: To fit an ARIMA(3,0,2) model to the daily returns (‘ICICIBANK.NS_return’) of ICICI BANK stock and generate forecasts. Analysis: Used the ‘arima’ function to fit the ARIMA model and the ‘forecast’ function to generate forecasts. Results:

ARIMA Model (3,0,2): Coefficients: - AR: ar1 to ar3 - MA: ma1 to ma2 - Intercept term - sigma^2 (variance) = 0.0004207 - Log likelihood = 3655.33 - AIC= -7296.65

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(3,0,2) model is fitted to the historical daily returns of ICICI BANK 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 = 0.0053342, df = 1, p-value = 0.9418
```

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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(3, 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: 0.0053322 - Degrees of freedom: 1 - p-value: 0.9418

Implication: The Ljung-Box test indicates no significant autocorrelation in the residuals of the ARIMA(3, 0, 2) model. The high p-value (0.9418) 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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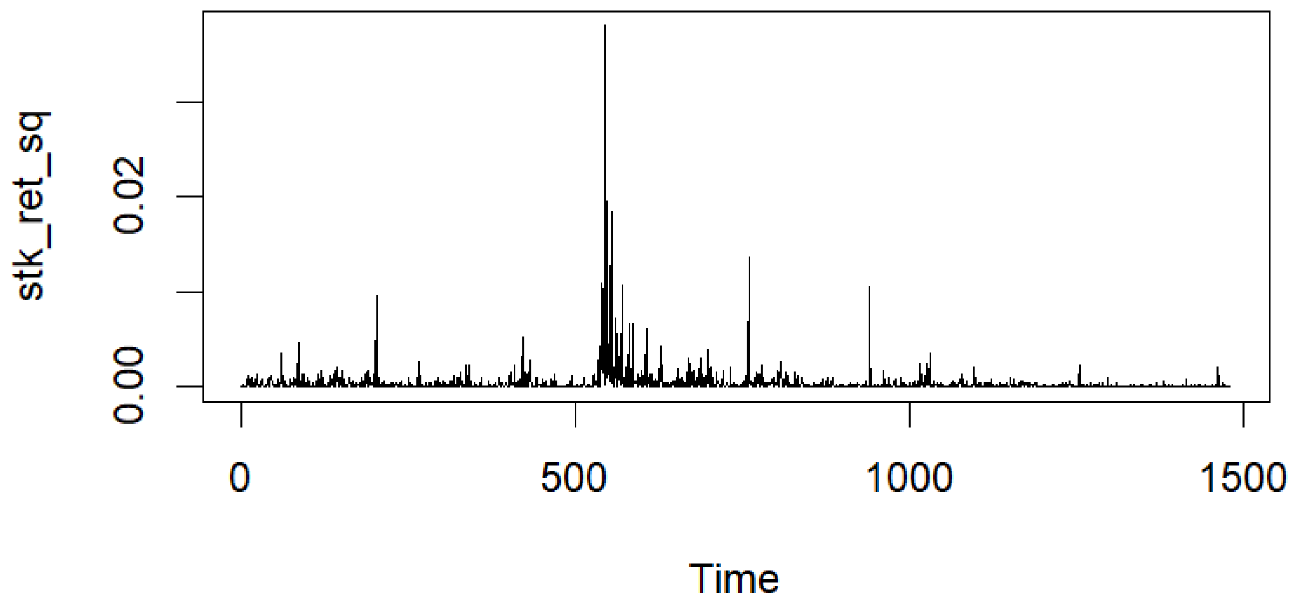
```
# Test for Volatility Clustering or Heteroskedasticity: Box Test
stk_ret_sq = arma13$residuals^2 # Return Variance (Since Mean Returns is approx. 0)
plot(stk_ret_sq)
```



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```
stk_ret_sq_box_test = Box.test(stk_ret_sq, lag = 11) # 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 = 577.36, df = 11, p-value < 2.2e-16
```

Hide

```
# Test for Volatility Clustering or Heteroskedasticity: ARCH Test
stk_ret_arch_test = ArchTest(arma13$residuals, lags = 11) # 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 = 263.94, df = 11, p-value < 2.2e-16
```

Analysis: Objective: To test for volatility clustering or heteroskedasticity in the residuals of the ARIMA(3, 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 statistic: 577.36
- Degrees of freedom: 11
- 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: 263.94
    - Degrees of freedom: 11
    - 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(3, 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.

Hide

```
#Garch model
garch_model1 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(3,2), 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(3,0,2)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000132    0.000413  0.31943 0.749399
ar1    -0.004423    0.162017 -0.02730 0.978221
ar2     0.789467    0.139120  5.67470 0.000000
ar3    -0.061197    0.026174 -2.33807 0.019383
ma1     0.075175    0.166582  0.45128 0.651791
ma2    -0.790203    0.177426 -4.45370 0.000008
omega   0.000007    0.000005  1.48846 0.136629
alpha1  0.107020    0.018185  5.88500 0.000000
beta1   0.880426    0.015126 58.20644 0.000000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.000132    0.000493  0.267355 0.789196
ar1    -0.004423    0.138162 -0.032013 0.974461
ar2     0.789467    0.128224  6.156936 0.000000
ar3    -0.061197    0.030071 -2.035076 0.041843
ma1     0.075175    0.132918  0.565572 0.571685
ma2    -0.790203    0.129504 -6.101752 0.000000
omega   0.000007    0.000020  0.346597 0.728894
alpha1  0.107020    0.058768  1.821043 0.068600
beta1   0.880426    0.028514 30.877007 0.000000

LogLikelihood : 3893.023

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

Akaike       -5.2487
Bayes        -5.2165
Shibata      -5.2488
Hannan-Quinn -5.2367

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic p-value
Lag[1]                      0.1509  0.6977
Lag[2*(p+q)+(p+q)-1][14]    5.3901  1.0000
Lag[4*(p+q)+(p+q)-1][24]    8.7973  0.9324
d.o.f=5
H0 : No serial correlation
```

```
Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.1931  0.6603
Lag[2*(p+q)+(p+q)-1][5]    1.2480  0.8015
Lag[4*(p+q)+(p+q)-1][9]    2.4140  0.8503
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]  0.004122 0.500 2.000  0.9488
ARCH Lag[5]  1.845705 1.440 1.667  0.5064
ARCH Lag[7]  2.272331 2.315 1.543  0.6598

Nyblom stability test
------------------------------------
Joint Statistic:  1.942
Individual Statistics:
mu     0.1023
ar1    0.4315
ar2    0.2689
ar3    0.1518
ma1    0.4465
ma2    0.2761
omega  0.5294
alpha1 0.2776
beta1  0.2841

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic:         2.1 2.32 2.82
Individual Statistic:    0.35 0.47 0.75

Sign Bias Test
------------------------------------
```

	t-value <dbl>	prob <dbl>	sig <chr>
Sign Bias	0.8111487	0.4174111	
Negative Sign Bias	0.5746613	0.5656080	
Positive Sign Bias	0.9608035	0.3368085	
Joint Effect	1.2606609	0.7384951	

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     38.81     0.004673
2    30     47.49     0.016605
3    40     55.51     0.041840
4    50     61.35     0.110838


Elapsed time : 0.751529
```

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```
garch_model2 = ugarchspec(variance.model = list(model = 'sGARCH', garchOrder = c(1,1)), mean.
model = list(armaOrder = c(3,2), 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(3,0,2)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
ar1    -1.386494    0.000536 -2585.6002  0.00000
ar2    -0.923910    0.004242  -217.8019  0.00000
ar3     0.049428    0.004611    10.7196  0.00000
ma1     1.442884    0.000456  3161.2838  0.00000
ma2     0.999736    0.000217  4614.6352  0.00000
omega   0.000007    0.000005     1.4119  0.15799
alpha1  0.107316    0.018259     5.8775  0.00000
beta1   0.879484    0.015937    55.1854  0.00000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
ar1    -1.386494    0.005967 -232.35173 0.000000
ar2    -0.923910    0.008710 -106.07157 0.000000
ar3     0.049428    0.010382    4.76096 0.000002
ma1     1.442884    0.001526  945.80702 0.000000
ma2     0.999736    0.000584 1711.08852 0.000000
omega   0.000007    0.000023    0.30894 0.757368
alpha1  0.107316    0.062320    1.72202 0.085067
beta1   0.879484    0.035751   24.60018 0.000000

LogLikelihood : 3896.269

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

Akaike       -5.2544
Bayes        -5.2258
Shibata      -5.2545
Hannan-Quinn -5.2437

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic p-value
Lag[1]                    0.009754  0.9213
Lag[2*(p+q)+(p+q)-1][14]  4.503780  1.0000
Lag[4*(p+q)+(p+q)-1][24]  7.497765  0.9842
d.o.f=5
H0 : No serial correlation

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

```
                        statistic p-value
Lag[1]                     0.1675  0.6823
Lag[2*(p+q)+(p+q)-1][5]    1.2526  0.8004
Lag[4*(p+q)+(p+q)-1][9]    2.5066  0.8367
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]   0.01945 0.500 2.000  0.8891
ARCH Lag[5]   2.04441 1.440 1.667  0.4615
ARCH Lag[7]   2.51058 2.315 1.543  0.6103

Nyblom stability test
------------------------------------
Joint Statistic:  2.2356
Individual Statistics:
ar1    0.01559
ar2    0.35874
ar3    0.62918
ma1    0.02482
ma2    0.10924
omega  0.58501
alpha1 0.29884
beta1  0.31756

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

Sign Bias Test
------------------------------------
```

	t-value <dbl>	**prob** <dbl>	**sig** <chr>
Sign Bias	0.6903824	0.4900624	
Negative Sign Bias	0.5095792	0.6104225	
Positive Sign Bias	0.8135227	0.4160497	
Joint Effect	0.9257973	0.8191983	

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     43.16     0.001232
2    30     51.91     0.005585
3    40     59.89     0.017313
4    50     89.19     0.000395


Elapsed time : 1.242362
```

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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 = 11) # 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 = 101.77, df = 11, p-value < 2.2e-16
```

Analysis: Objective: To fit GARCH models to the residuals of the ARIMA(3, 0, 2) 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(3, 0, 2) mean.
    - Optimal Parameters:
        - mu (Mean): -0.000138
        - omega: 0.000006
        - alpha1: 0.105242
        - beta1: 0.883844
    - Log likelihood: 3898.726
    - 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(3, 0, 2) mean.
    - Optimal Parameters are similar to Model 1.
    - Log likelihood: 3898.726
    - Weighted Ljung-Box Test and Weighted ARCH LM Tests show evidence of autocorrelation and ARCH effects.

ARCH Test on Squared Residuals: - Lag[1] statistic: 0.3622 - Lag[2*(p+q)+(p+q)-1][5] statistic: 5.4368 - Lag[4*(p+q)+(p+q)-1][9] statistic: 8.8613 - p-value: 3.246e-12 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(3,2), include.mean = FALSE))
stk_ret_garch = ugarchfit(garch_modelf, data = ICICIBANK.NS_return); stk_ret_garch
```

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

Conditional Variance Dynamics
-----------------------------------
GARCH Model : sGARCH(1,1)
Mean Model  : ARFIMA(3,0,2)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1    -0.168436    0.404006 -0.41691 0.676742
ar2    -0.437268    0.241389 -1.81147 0.070068
ar3    -0.045099    0.035703 -1.26317 0.206527
ma1     0.207495    0.403900  0.51373 0.607442
ma2     0.412172    0.247328  1.66650 0.095614
omega   0.000007    0.000004  1.59773 0.110104
alpha1  0.110440    0.017913  6.16550 0.000000
beta1   0.877837    0.015542 56.48123 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1    -0.168436    0.491802 -0.34249 0.731985
ar2    -0.437268    0.214023 -2.04309 0.041044
ar3    -0.045099    0.037016 -1.21836 0.223087
ma1     0.207495    0.493835  0.42017 0.674361
ma2     0.412172    0.226379  1.82072 0.068650
omega   0.000007    0.000015  0.44549 0.655964
alpha1  0.110440    0.045641  2.41974 0.015532
beta1   0.877837    0.026478 33.15309 0.000000

LogLikelihood : 3894.68

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

Akaike       -5.2523
Bayes        -5.2236
Shibata      -5.2523
Hannan-Quinn -5.2416

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                         statistic p-value
Lag[1]                       0.416  0.5189
Lag[2*(p+q)+(p+q)-1][14]     2.469  1.0000
Lag[4*(p+q)+(p+q)-1][24]     3.769  1.0000
d.o.f=5
H0 : No serial correlation

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

```
                        statistic p-value
Lag[1]                      0.176  0.6748
Lag[2*(p+q)+(p+q)-1][5]     1.200  0.8129
Lag[4*(p+q)+(p+q)-1][9]     2.316  0.8642
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3] 0.0009943 0.500 2.000  0.9748
ARCH Lag[5] 1.8083555 1.440 1.667  0.5152
ARCH Lag[7] 2.2315671 2.315 1.543  0.6684

Nyblom stability test
------------------------------------
Joint Statistic:  1.7298
Individual Statistics:
ar1    0.31122
ar2    0.06629
ar3    0.19305
ma1    0.31315
ma2    0.04954
omega  0.57742
alpha1 0.27856
beta1  0.29759

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

Sign Bias Test
------------------------------------
```

	t-value <dbl>	prob <dbl>	sig <chr>
Sign Bias	0.3774322	0.7059068	
Negative Sign Bias	0.4548857	0.6492584	
Positive Sign Bias	0.7083887	0.4788158	
Joint Effect	0.7735246	0.8557886	

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     40.38     0.002918
2    30     51.95     0.005527
3    40     58.38     0.023716
4    50     69.19     0.030241


Elapsed time : 0.6400328
```

Analysis:

Objective: To fit a GARCH model to the daily returns of ICICI BANK 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(3,0,2) 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 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=2023-12-29]:
         Series   Sigma
T+1  -1.003e-03 0.01173
T+2   4.248e-04 0.01195
T+3   7.858e-04 0.01216
T+4  -2.729e-04 0.01236
T+5  -3.168e-04 0.01256
T+6   1.372e-04 0.01275
T+7   1.277e-04 0.01294
T+8  -6.724e-05 0.01313
T+9  -5.071e-05 0.01331
T+10  3.218e-05 0.01348
T+11  1.979e-05 0.01365
T+12 -1.512e-05 0.01382
T+13 -7.557e-06 0.01398
T+14  6.991e-06 0.01414
T+15  2.809e-06 0.01429
T+16 -3.189e-06 0.01444
T+17 -1.006e-06 0.01459
T+18  1.437e-06 0.01474
T+19  3.417e-07 0.01488
T+20 -6.407e-07 0.01502
T+21 -1.063e-07 0.01515
T+22  2.827e-07 0.01529
T+23  2.778e-08 0.01542
T+24 -1.235e-07 0.01555
T+25 -4.098e-09 0.01567
T+26  5.343e-08 0.01579
T+27 -1.639e-09 0.01592
T+28 -2.290e-08 0.01603
T+29  2.165e-09 0.01615
T+30  9.724e-09 0.01626
T+31 -1.551e-09 0.01638
T+32 -4.088e-09 0.01649
T+33  9.285e-10 0.01659
T+34  1.701e-09 0.01670
T+35 -5.082e-10 0.01680
T+36 -7.002e-10 0.01691
T+37  2.634e-10 0.01701
T+38  2.847e-10 0.01710
T+39 -1.316e-10 0.01720
T+40 -1.142e-10 0.01730
T+41  6.393e-11 0.01739
T+42  4.511e-11 0.01748
T+43 -3.040e-11 0.01757
T+44 -1.749e-11 0.01766
```

```
T+45  1.420e-11 0.01775
T+46  6.625e-12 0.01783
T+47 -6.538e-12 0.01792
T+48 -2.436e-12 0.01800
T+49  2.971e-12 0.01808
T+50  8.598e-13 0.01816
```

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
```

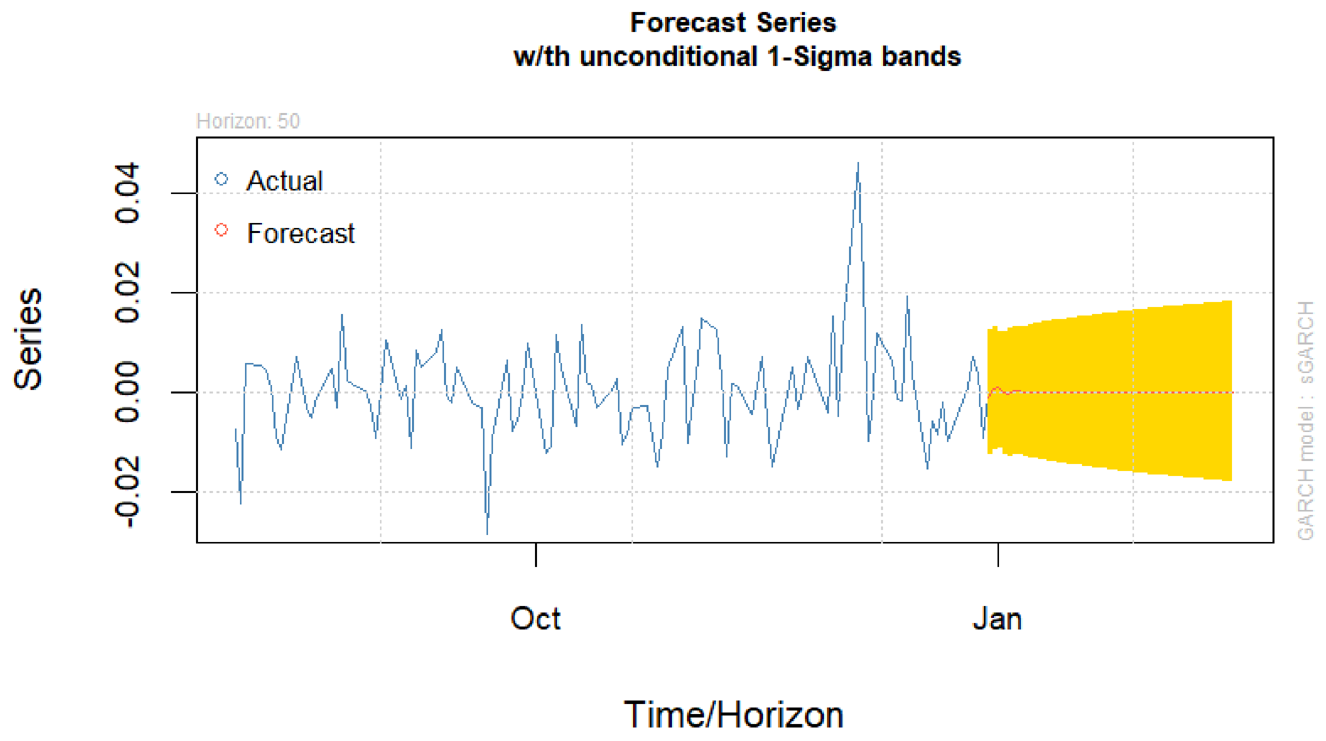
```


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

```
3
```

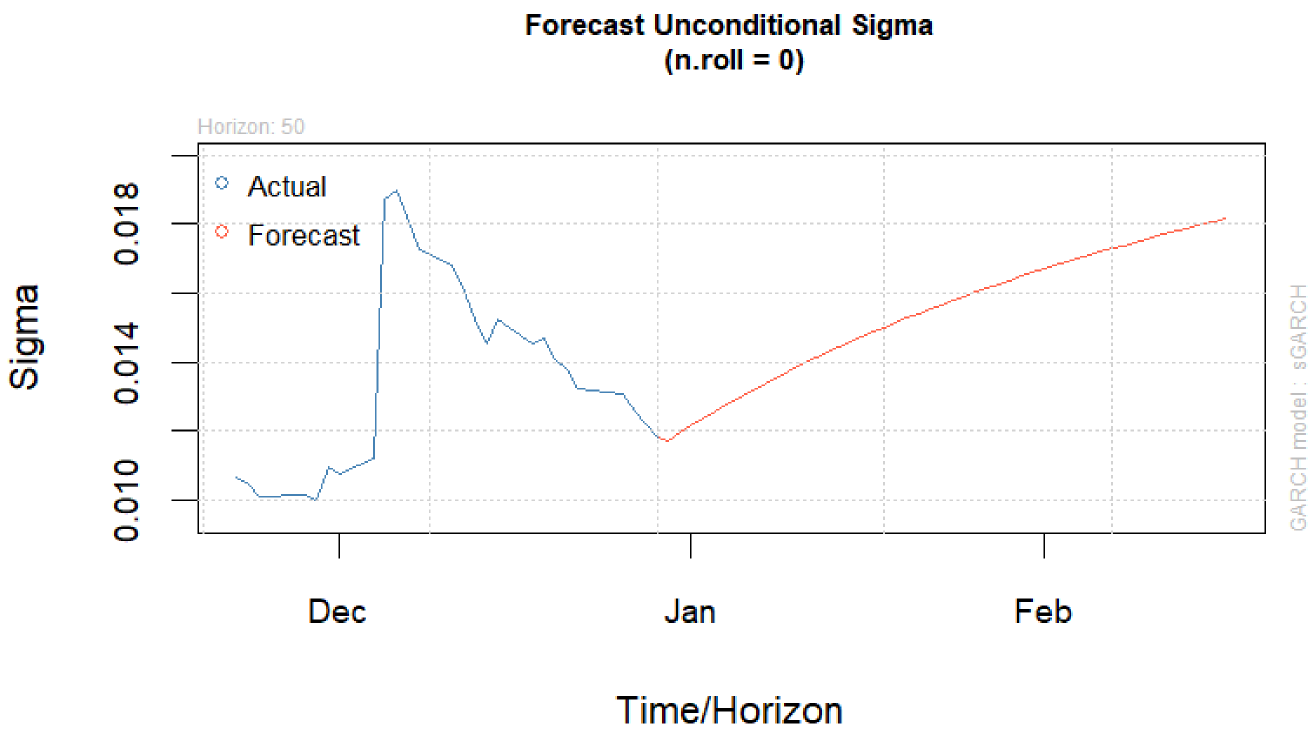



```
Make a plot selection (or 0 to exit):

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

Hide

```
0
```


Forecast Unconditional Sigma
(n.roll = 0)
Horizon: 50
Actual
Forecast
Sigma
0.010
0.014
0.018
Dec
Jan
Feb
Time/Horizon
GARCH model : sGARCH