Code

Ratik_29A_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*.

Show

```
<!-- rnb-source-end -->

<!-- rnb-output-begin eyJkYXRhIjoiRXJyb3I6IGF0dGVtcHQgdG8gdXNlIHplcm8tbGVuZ3RoIHZhcml
hYmxlIG5hbWVcbiJ9 -->
```

Error: attempt to use zero-length variable name

```
<!-- rnb-output-end -->

<!-- rnb-chunk-end -->


<!-- rnb-text-begin -->

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


<!-- rnb-text-end -->


<!-- rnb-chunk-begin -->


<!-- rnb-source-begin eyJkYXRhIjoiYGBgclxuYGBgXG5cbmBgYCJ9 -->

```r
```
```

```
<!-- rnb-source-end -->

<!-- rnb-output-begin eyJkYXRhIjoiRXJyb3I6IGF0dGVtcHQgdG8gdXNlIHplcm8tbGVuZ3RoIHZhcml
hYmxlIG5hbWVcbiJ9 -->
```

Error: attempt to use zero-length variable name

````
<!-- rnb-output-end -->

<!-- rnb-chunk-end -->


<!-- rnb-text-begin -->

Analysis:

Objective: To conduct an Augmented Dickey-Fuller (ADF) test for stationarity on the d
aily returns of NESTLEIND.NS stock.
Analysis: Performed the ADF test using the 'adf.test' function and obtained results.
Result:
The Augmented Dickey-Fuller test for stationarity on NESTLEIND.NS daily returns yield
s the following results:
  - Dickey-Fuller statistic: -11.276
  - Lag order: 11
  - p-value: 0.01
  - Alternative hypothesis: Stationary

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



<!-- rnb-text-end -->


<!-- rnb-chunk-begin -->


<!-- rnb-source-begin eyJkYXRhIjoiYGBgclxuI0F1dG9jb3JyZWxhdGlvbiB0ZXN0XG4jIExqdW5nLUJ
veCBUZXN0IGZvciBBdXRvY29ycmVsYXRpb25cbmxiX3Rlc3RfZHMgPSBCb3gudGVzdChORVNUTEVJTkQuTlNf
cmV0dXJuKTsgbGJfdGVzdF9kc1xuYGBgIn0= -->

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

```
    Box-Pierce test

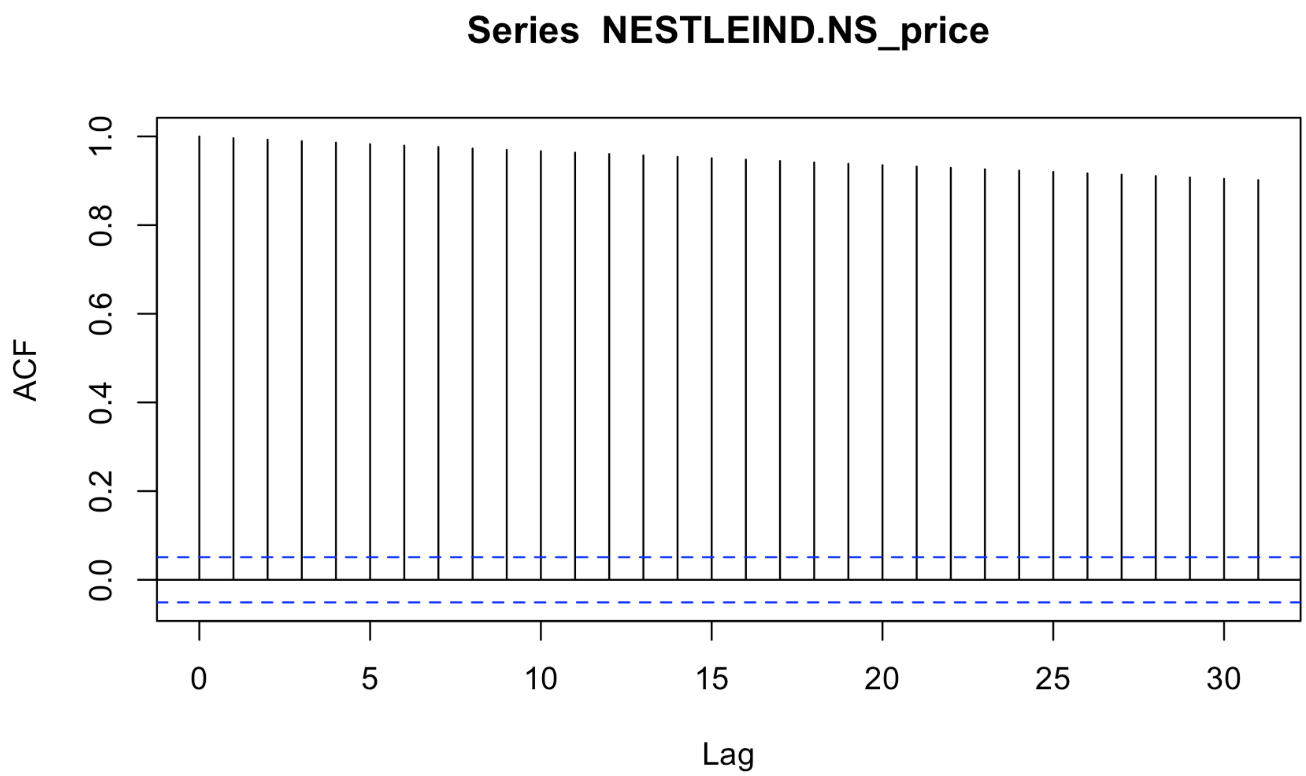
data:  NESTLEIND.NS_return
X-squared = 5.2778, df = 1, p-value = 0.0216
```

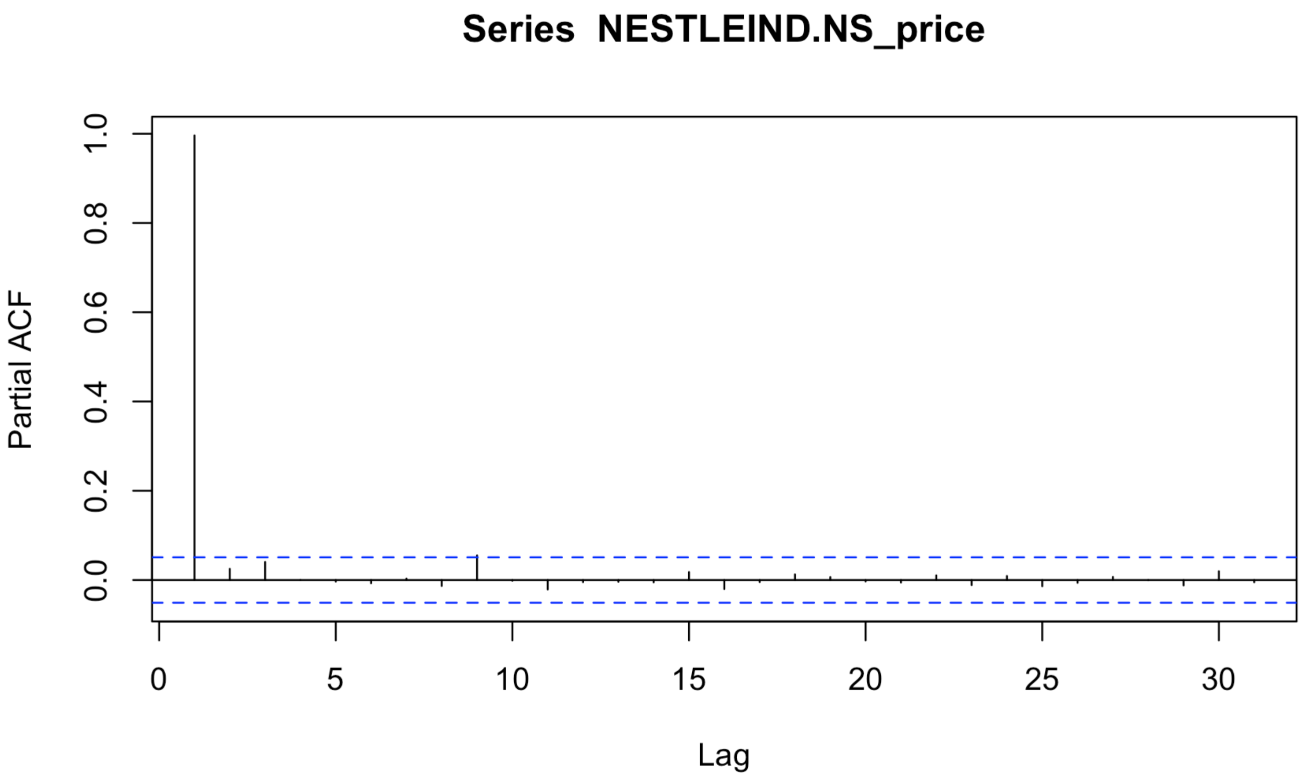
Analysis:

Objective: To perform a Ljung-Box test for autocorrelation on the daily returns of NESTLEIND.NS stock. Analysis: Conducted the Ljung-Box test using the ‘Box.test’ function and obtained results. Result: The Ljung-Box test for autocorrelation on NESTLEIND.NS daily returns yields the following results: - X-squared statistic: 5.2777 - Degrees of freedom: 1 - p-value: < 0.0216

Implication: The Ljung-Box test indicates significant autocorrelation in the NESTLEIND.NS stock daily returns. The small p-value (< 0.0216) 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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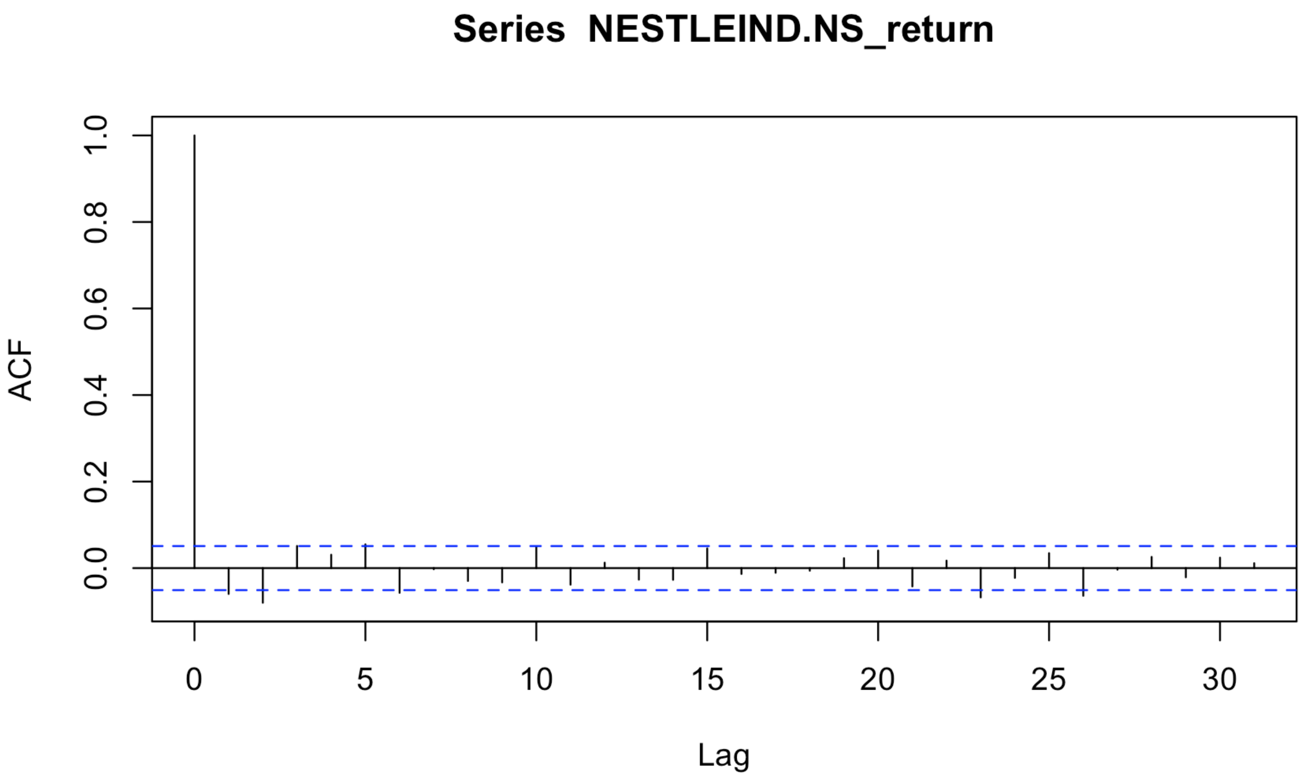
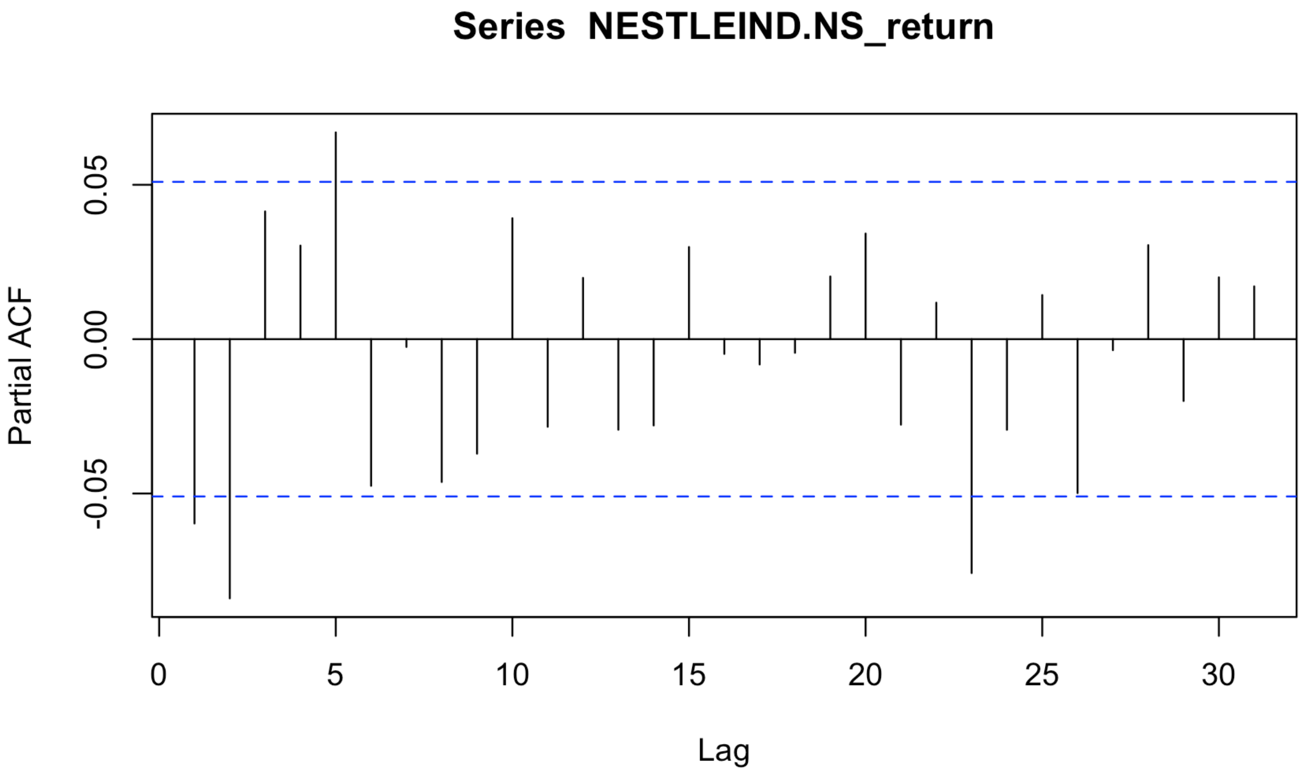
```
acf(NESTLEIND.NS_price) # ACF of JJ Series
pacf(NESTLEIND.NS_price) # PACF of JJ Series


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



Hide

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



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```
arma_pq_ds = auto.arima(NESTLEIND.NS_return); arma_pq_ds
```

```
Series: NESTLEIND.NS_return
ARIMA(4,0,5) with non-zero mean

Coefficients:
          ar1      ar2      ar3      ar4     ma1     ma2     ma3     ma4     ma5    me
an
      -0.9539  -0.3448  -0.2026  -0.5244  0.8988  0.2138  0.1706  0.5901  0.0671  1e-
03
s.e.   0.1726   0.2817   0.2528   0.1451  0.1732  0.2649  0.2253  0.1252  0.0350  4e-
04

sigma^2 = 0.0002098:  log likelihood = 4172.06
AIC=-8322.11   AICc=-8321.93   BIC=-8263.81
```

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

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

Coefficients:
         ar1      ar2      ma1     ma2   drift
      0.6985  -0.7192  -0.7801  0.7071  1.3649
s.e.  0.1425   0.0839   0.1515  0.0859  0.4911

sigma^2 = 434.2:  log likelihood = -6591.99
AIC=13195.98   AICc=13196.04   BIC=13227.78
```

Analysis:

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

For Daily Returns (‘NESTLEIND.NS_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) = 0.0002098 - Log likelihood = 4172.06 - AIC=-8322.11 AICc=-8321.93 BIC=-8263.81

For Adjusted Closing Prices (‘NESTLEIND.NS_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) = 434.2 - Log likelihood = -6591.99 - AIC = 13195.98, AICc = 13196.03, BIC = 13227.78

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

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```
arma13 = arima(NESTLEIND.NS_return, order = c(5, 0, 4)); arma13
```

```


Call:
arima(x = NESTLEIND.NS_return, order = c(5, 0, 4))

Coefficients:
          ar1      ar2      ar3      ar4     ar5     ma1     ma2     ma3     ma4  int
ercept
      -0.8625  -0.2815  -0.1937  -0.5004  0.0639  0.8071  0.1578  0.1712  0.5652
1e-03
s.e.   0.1680   0.2733   0.2439   0.1547  0.0348  0.1673  0.2576  0.2174  0.1324
4e-04

sigma^2 estimated as 0.0002084:  log likelihood = 4171.99,  aic = -8321.99
```

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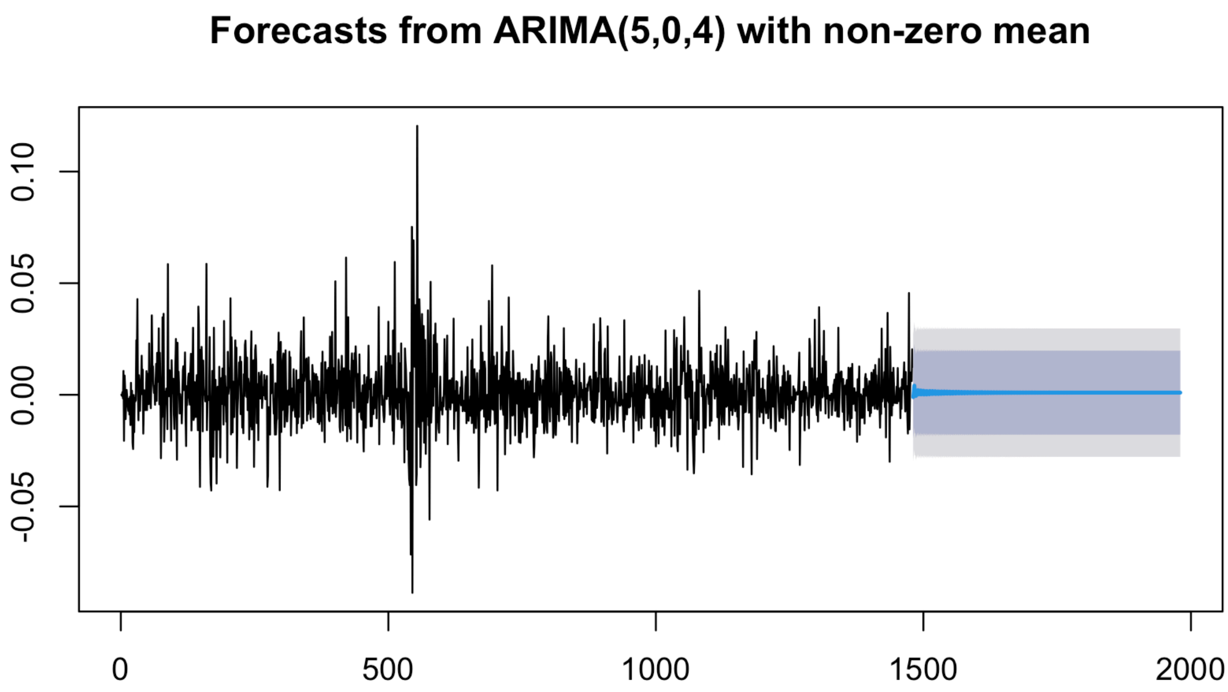
```
ds_fpq = forecast(arma13, h = 500)
plot(ds_fpq)
```



Analysis:

Objective: To fit an ARIMA(5, 0, 4) model to the daily returns (‘NESTLEIND.NS_return’) of NESTLEIND.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 (5, 0, 4): Coefficients: - AR: ar1 to ar5 - MA: ma1 to ma4 - Intercept term - sigma^2 estimated as 0.0002084: log likelihood = 4172, aic = -8322 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 NESTLEIND.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.

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```
lb_test_ds_A = Box.test(arma13$residuals); lb_test_ds_A
```

```

	Box-Pierce test

data:  arma13$residuals
X-squared = 8.1429e-05, df = 1, p-value = 0.9928
```

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:

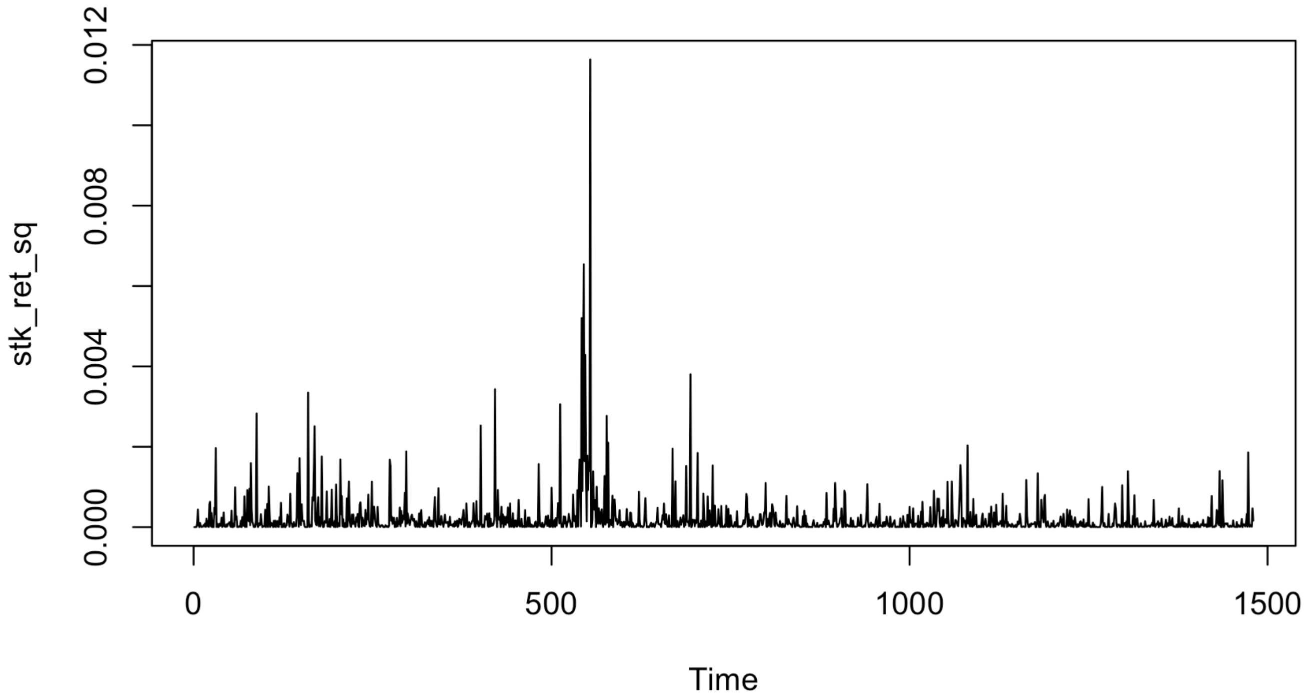
Ljung-Box Test for Autocorrelation on Residuals:

X-squared = 8.1429e-05, df = 1, p-value = 0.9928

Implication: The Ljung-Box test indicates no significant autocorrelation in the residuals of the ARIMA(5, 0, 4) model. The high p-value (0.9928) 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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```
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 Correlated
stk_ret_sq_box_test # Inference : Return Variance Series is Heteroskedastic (Has Volatility Clustering)
```

```
	Box-Pierce test

data:  stk_ret_sq
X-squared = 520.09, df = 10, p-value < 2.2e-16
```

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```
# 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 Clus
tering)
```

```


    ARCH LM-test; Null hypothesis: no ARCH effects

data:  arma13$residuals
Chi-squared = 214.89, 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 = 520.09, 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 = 214.89, df = 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.

Hide

```
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     -0.000107    0.000336  -0.3202  0.74882
omega   0.000008    0.000000  18.3258  0.00000
alpha1  0.063346    0.005384  11.7648  0.00000
beta1   0.894932    0.008562 104.5290  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.000107    0.000338 -0.31774  0.75068
omega   0.000008    0.000001 10.12415  0.00000
alpha1  0.063346    0.004695 13.49120  0.00000
beta1   0.894932    0.010196 87.77367  0.00000

LogLikelihood : 4266.191

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

Akaike       -5.7597
Bayes        -5.7454
Shibata      -5.7597
Hannan-Quinn -5.7544

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.05121  0.8210
Lag[2*(p+q)+(p+q)-1][2]   0.47904  0.7035
Lag[4*(p+q)+(p+q)-1][5]   2.56936  0.4913
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.360  0.2436
Lag[2*(p+q)+(p+q)-1][5]     2.062  0.6037
Lag[4*(p+q)+(p+q)-1][9]     4.401  0.5223
d.o.f=2

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

```
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.6777 0.500 2.000  0.4104
ARCH Lag[5]    1.2503 1.440 1.667  0.6604
ARCH Lag[7]    2.9866 2.315 1.543  0.5161

Nyblom stability test
------------------------------------
Joint Statistic:  22.0386
Individual Statistics:
mu     0.1461
omega  4.3633
alpha1 0.5998
beta1  0.7088

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	1.0364900	0.300143504	
Negative Sign Bias	2.6407934	0.008358536	***
Positive Sign Bias	0.1013824	0.919260708	
Joint Effect	7.3069062	0.062733044	*

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     77.68    4.662e-09
2    30     96.99    2.952e-09
3    40    104.97    5.832e-08
4    50    112.84    6.042e-07


Elapsed time : 0.2001059
```

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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     0.020899    0.028053  7.4498e-01  0.45628
ar2    -0.058183    0.010736 -5.4195e+00  0.00000
ar3     0.025519    0.027392  9.3162e-01  0.35153
ar4     0.931297    0.010307  9.0354e+01  0.00000
ma1    -0.027895    0.037281 -7.4825e-01  0.45431
ma2     0.059522    0.001002  5.9410e+01  0.00000
ma3    -0.034248    0.023692 -1.4456e+00  0.14830
ma4    -0.942482    0.000078 -1.2113e+04  0.00000
ma5    -0.004458    0.026934 -1.6550e-01  0.86855
omega   0.000008    0.000000  1.5492e+01  0.00000
alpha1  0.060477    0.005255  1.1509e+01  0.00000
beta1   0.900767    0.008280  1.0878e+02  0.00000

Robust Standard Errors:
        Estimate  Std. Error     t value Pr(>|t|)
ar1     0.020899    0.020152  1.0371e+00 0.299709
ar2    -0.058183    0.011021 -5.2791e+00 0.000000
ar3     0.025519    0.018501  1.3793e+00 0.167800
ar4     0.931297    0.009549  9.7530e+01 0.000000
ma1    -0.027895    0.031163 -8.9512e-01 0.370721
ma2     0.059522    0.001036  5.7431e+01 0.000000
ma3    -0.034248    0.016359 -2.0935e+00 0.036304
ma4    -0.942482    0.000071 -1.3198e+04 0.000000
ma5    -0.004458    0.027387 -1.6276e-01 0.870703
omega   0.000008    0.000001  8.5209e+00 0.000000
alpha1  0.060477    0.004399  1.3747e+01 0.000000
beta1   0.900767    0.009816  9.1770e+01 0.000000

LogLikelihood : 4270.661

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

Akaike       -5.7549
Bayes        -5.7120
Shibata      -5.7551
Hannan-Quinn -5.7389

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

```
Lag[1]                          0.1921  0.6611
Lag[2*(p+q)+(p+q)-1][26]        9.7359  1.0000
Lag[4*(p+q)+(p+q)-1][44]       16.4544  0.9680
d.o.f=9
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.9248  0.3362
Lag[2*(p+q)+(p+q)-1][5]    1.4355  0.7558
Lag[4*(p+q)+(p+q)-1][9]    3.6920  0.6414
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]     0.441 0.500 2.000  0.5066
ARCH Lag[5]     1.032 1.440 1.667  0.7236
ARCH Lag[7]     2.795 2.315 1.543  0.5531

Nyblom stability test
------------------------------------
Joint Statistic:  19.9501
Individual Statistics:
ar1    0.03524
ar2    0.08029
ar3    0.05000
ar4    0.11097
ma1    0.04597
ma2    0.08457
ma3    0.04964
ma4    0.09192
ma5    0.04639
omega  3.65095
alpha1 0.59236
beta1  0.70169

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	0.8222160	0.41108689	
Negative Sign Bias	2.2464470	0.02482283	**
Positive Sign Bias	0.1666323	0.86768219	
Joint Effect	5.4631656	0.14085840	

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20      69.0    1.348e-07
2    30      81.3    7.470e-07
3    40     102.5    1.291e-07
4    50     142.3    4.966e-11


Elapsed time : 0.4108779
```

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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 Clu
stering)
```

```
    ARCH LM-test; Null hypothesis: no ARCH effects

data:  gar_resd
Chi-squared = 6.5372, df = 1, p-value = 0.01056
```

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 = NESTLEIND.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    -1.103740    0.016796  -65.714        0
ar2    -0.873307    0.040315  -21.662        0
ar3    -0.836997    0.039988  -20.931        0
ar4    -0.829522    0.017868  -46.426        0
ma1     1.048849    0.002737  383.277        0
ma2     0.760029    0.019261   39.459        0
ma3     0.715485    0.011540   61.998        0
ma4     0.749961    0.000181 4134.244        0
ma5    -0.027693    0.001334  -20.754        0
omega   0.000008    0.000000   18.500        0
alpha1  0.065691    0.006194   10.605        0
beta1   0.892730    0.008757  101.950        0

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
ar1    -1.103740    0.017818  -61.9441        0
ar2    -0.873307    0.048088  -18.1607        0
ar3    -0.836997    0.049272  -16.9873        0
ar4    -0.829522    0.021007  -39.4873        0
ma1     1.048849    0.003309  316.9718        0
ma2     0.760029    0.022391   33.9441        0
ma3     0.715485    0.016137   44.3375        0
ma4     0.749961    0.000127 5895.6259        0
ma5    -0.027693    0.002351  -11.7769        0
omega   0.000008    0.000001   10.5021        0
alpha1  0.065691    0.006753    9.7282        0
beta1   0.892730    0.011123   80.2576        0

LogLikelihood : 4267.484

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

Akaike       -5.7507
Bayes        -5.7077
Shibata      -5.7508
Hannan-Quinn -5.7346

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

```
Lag[1]                      0.07976  0.7776
Lag[2*(p+q)+(p+q)-1][26]   6.41522  1.0000
Lag[4*(p+q)+(p+q)-1][44]  12.86564  0.9994
d.o.f=9
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.027  0.3108
Lag[2*(p+q)+(p+q)-1][5]     1.751  0.6782
Lag[4*(p+q)+(p+q)-1][9]     3.961  0.5955
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.8947 0.500 2.000  0.3442
ARCH Lag[5]    1.3241 1.440 1.667  0.6398
ARCH Lag[7]    2.9859 2.315 1.543  0.5162

Nyblom stability test
------------------------------------
Joint Statistic:  21.858
Individual Statistics:
ar1    0.09429
ar2    0.20097
ar3    0.17053
ar4    0.05561
ma1    0.11016
ma2    0.28523
ma3    0.30449
ma4    0.10293
ma5    0.03577
omega  4.14455
alpha1 0.59940
beta1  0.73125

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	0.2461124	0.80562944	
Negative Sign Bias	2.4979552	0.01259938	**
Positive Sign Bias	0.2438965	0.80734493	
Joint Effect	8.0801981	0.04438301	**

4 rows

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     65.78    4.551e-07
2    30     92.81    1.336e-08
3    40    109.14    1.466e-08
4    50    116.96    1.748e-07


Elapsed time : 0.452879
```

Analysis:

Objective: To fit a GARCH model to the daily returns of NESTLEIND.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 (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 NESTLEIND.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.

Hide

```
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  -2.363e-03 0.01455
T+2   1.824e-04 0.01453
T+3   2.068e-03 0.01451
T+4  -8.687e-05 0.01450
T+5  -3.230e-04 0.01448
T+6  -1.450e-03 0.01447
T+7   2.396e-04 0.01445
T+8   1.344e-03 0.01444
T+9  -2.113e-04 0.01442
T+10  6.158e-05 0.01441
T+11 -1.207e-03 0.01440
T+12  3.406e-04 0.01439
T+13  8.022e-04 0.01437
T+14 -2.234e-04 0.01436
T+15  2.624e-04 0.01435
T+16 -1.048e-03 0.01434
T+17  4.496e-04 0.01433
T+18  3.850e-04 0.01432
T+19 -1.578e-04 0.01431
T+20  3.313e-04 0.01431
T+21 -9.231e-04 0.01430
T+22  5.422e-04 0.01429
T+23  6.126e-05 0.01428
T+24 -4.333e-05 0.01427
T+25  3.062e-04 0.01427
T+26 -8.012e-04 0.01426
T+27  6.024e-04 0.01425
T+28 -1.855e-04 0.01425
T+29  9.531e-05 0.01424
T+30  2.173e-04 0.01424
T+31 -6.674e-04 0.01423
T+32  6.211e-04 0.01423
T+33 -3.635e-04 0.01422
T+34  2.373e-04 0.01422
T+35  8.941e-05 0.01421
T+36 -5.168e-04 0.01421
T+37  5.953e-04 0.01420
T+38 -4.774e-04 0.01420
T+39  3.654e-04 0.01420
T+40 -5.599e-05 0.01419
T+41 -3.516e-04 0.01419
T+42  5.271e-04 0.01419
T+43 -5.310e-04 0.01418
T+44  4.665e-04 0.01418
```

```
T+45 -2.007e-04 0.01418
T+46 -1.787e-04 0.01417
T+47  4.225e-04 0.01417
T+48 -5.293e-04 0.01417
T+49  5.312e-04 0.01416
T+50 -3.295e-04 0.01416
```

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
```

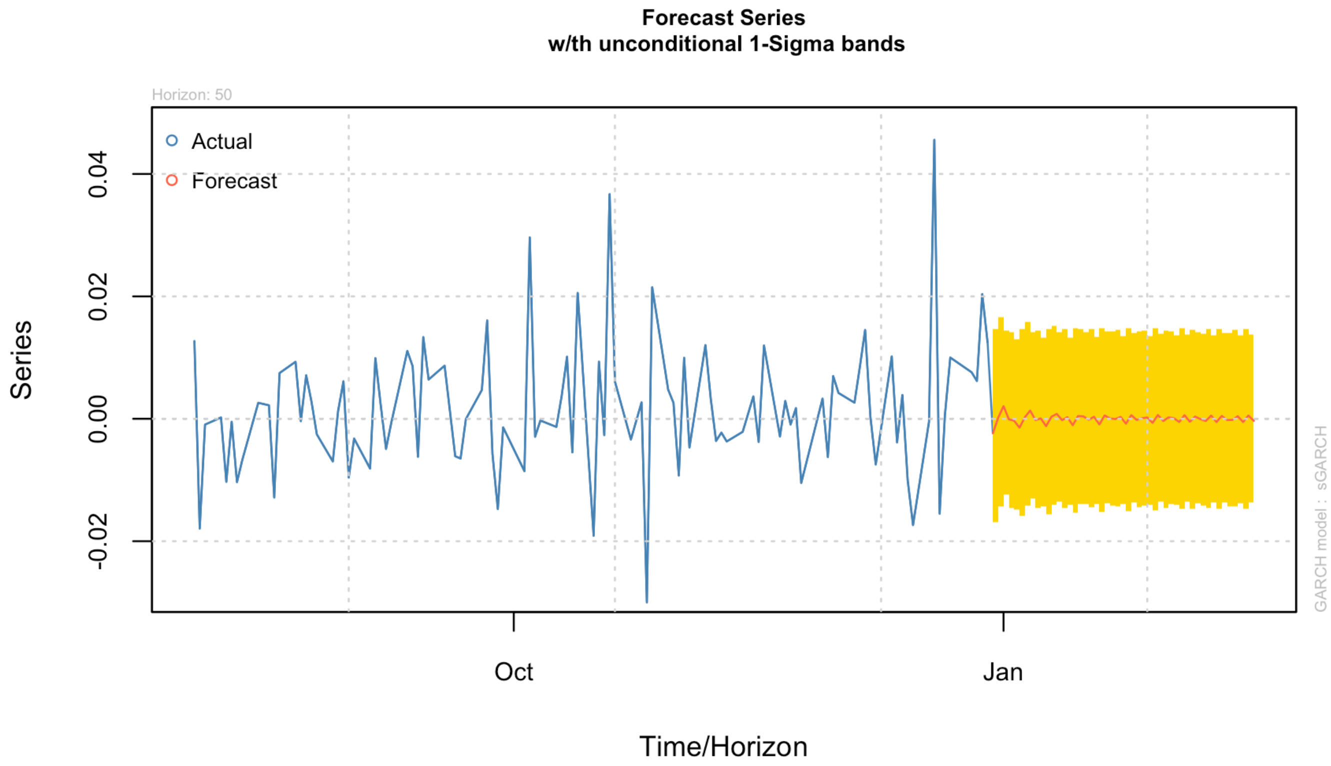
```


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
```



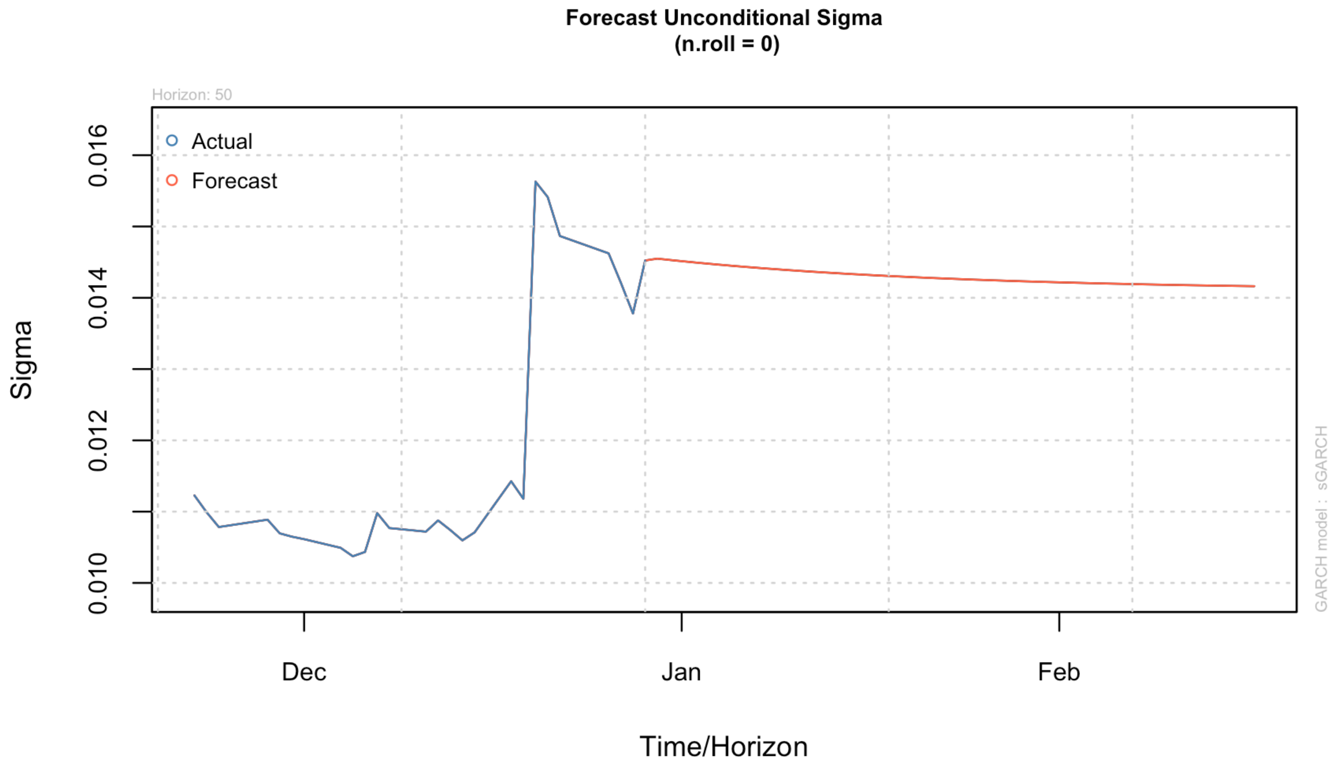

```
Make a plot selection (or 0 to exit):

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

Hide

```
4
```

```
Error in .plot.garchforecast.4(x, n.roll) :
n.roll less than 5!...does not make sense to provide this plot.
```


Forecast Unconditional Sigma
(n.roll = 0)
Horizon: 50
Actual
Forecast
Sigma
0.010
0.012
0.014
0.016
Dec
Jan
Feb
Time/Horizon
GARCH model : sGARCH