Accenture Stock Time Series Analysis

RTSM
MBA-BA

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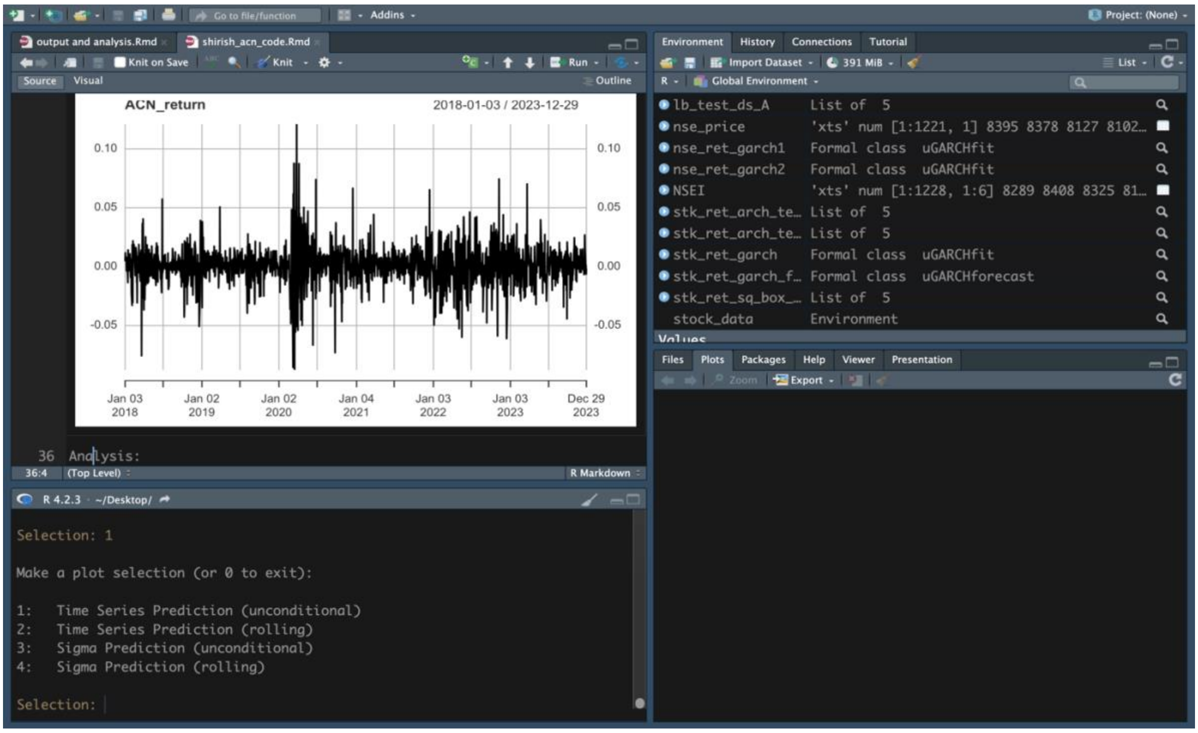
Objective: To analyze the daily returns of Accenture stock from 2018-01-01 to 2023-12-31.

Analysis: Extracted the adjusted closing prices of ACN stock, calculated daily returns, and visualized them.

Result: The 'ACN_return' plot displays the daily returns of ACN stock over the specified period.

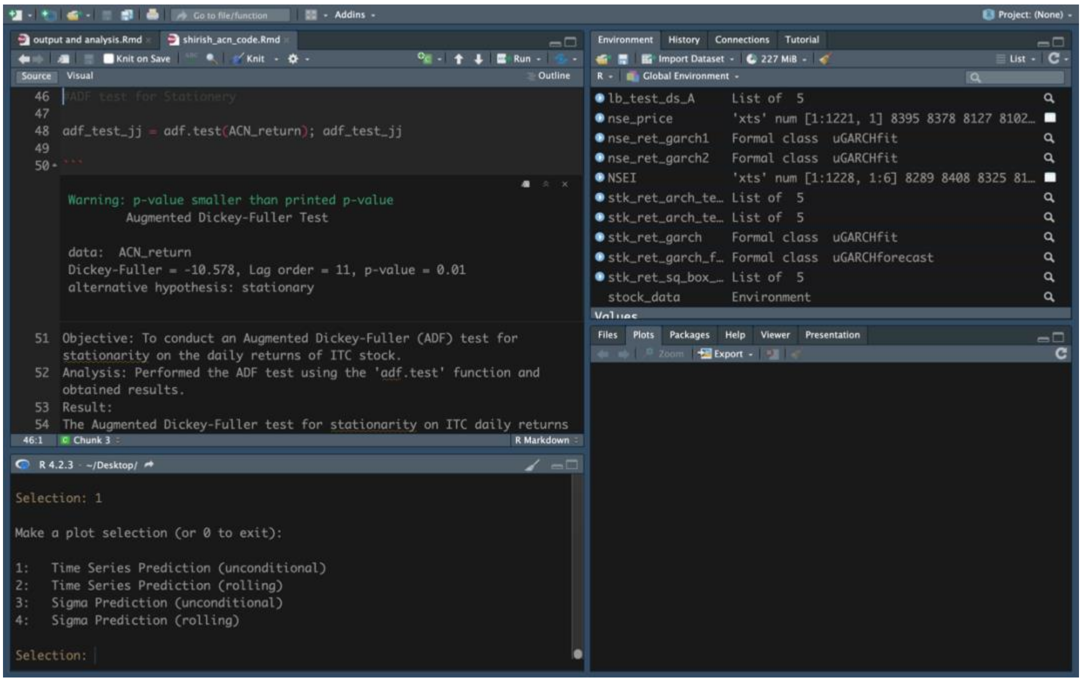


Implication: The plot indicates the volatility and direction of daily returns for ACN stock during the given timeframe. Observations from the plot can help investors understand the historical performance and risk associated with ITC stock.

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:

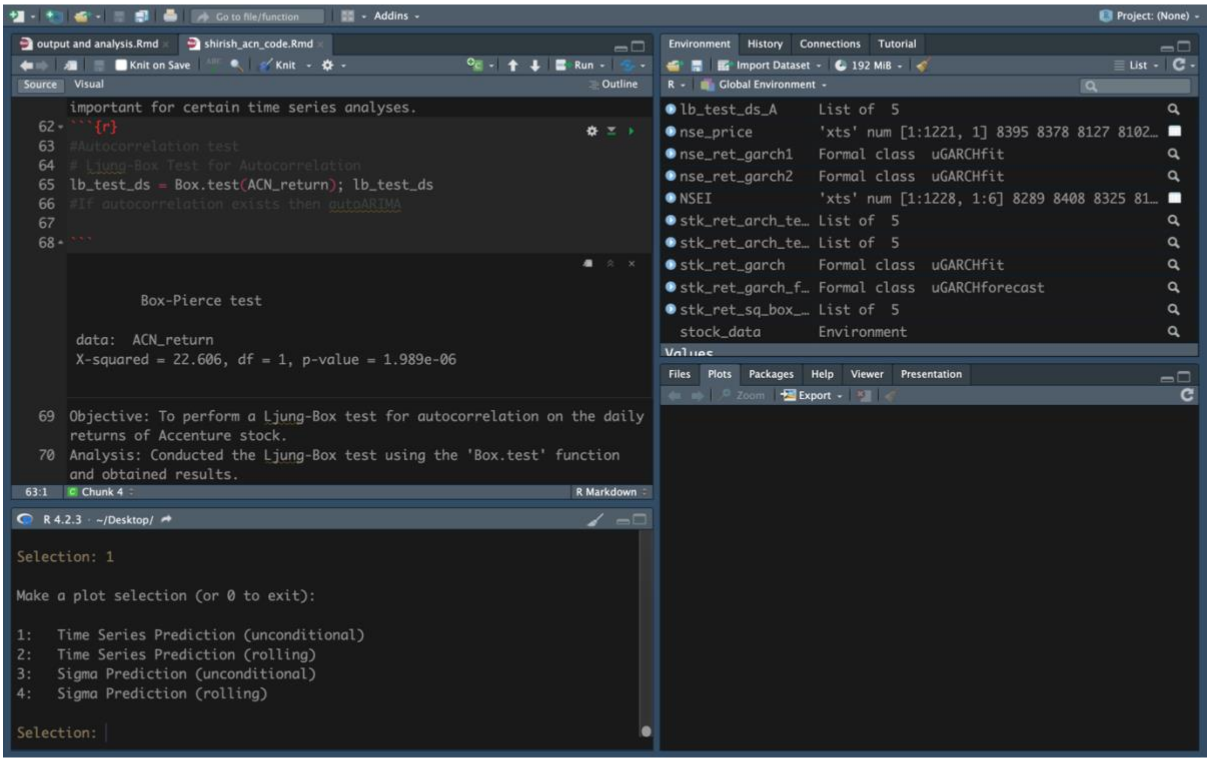
- **Dickey-Fuller statistic: -10.578**
- **Lag order: 11**
- **p-value: 0.01**
- **Alternative hypothesis: Stationary**

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



Objective: To perform a Ljung-Box test for autocorrelation on the daily returns of Accenture stock.
Analysis: Conducted the Ljung-Box test using the 'Box.test' function and obtained results.
Result:
The Ljung-Box test for autocorrelation on Accenture daily returns yields the following results:
X-squared = 22.606
df = 1
p-value = 1.989e-06
Implication:
The Ljung-Box test indicates significant autocorrelation in the Accenture stock daily returns. The small p-value (< 1.989e-06) suggests evidence against the null hypothesis of no autocorrelation.

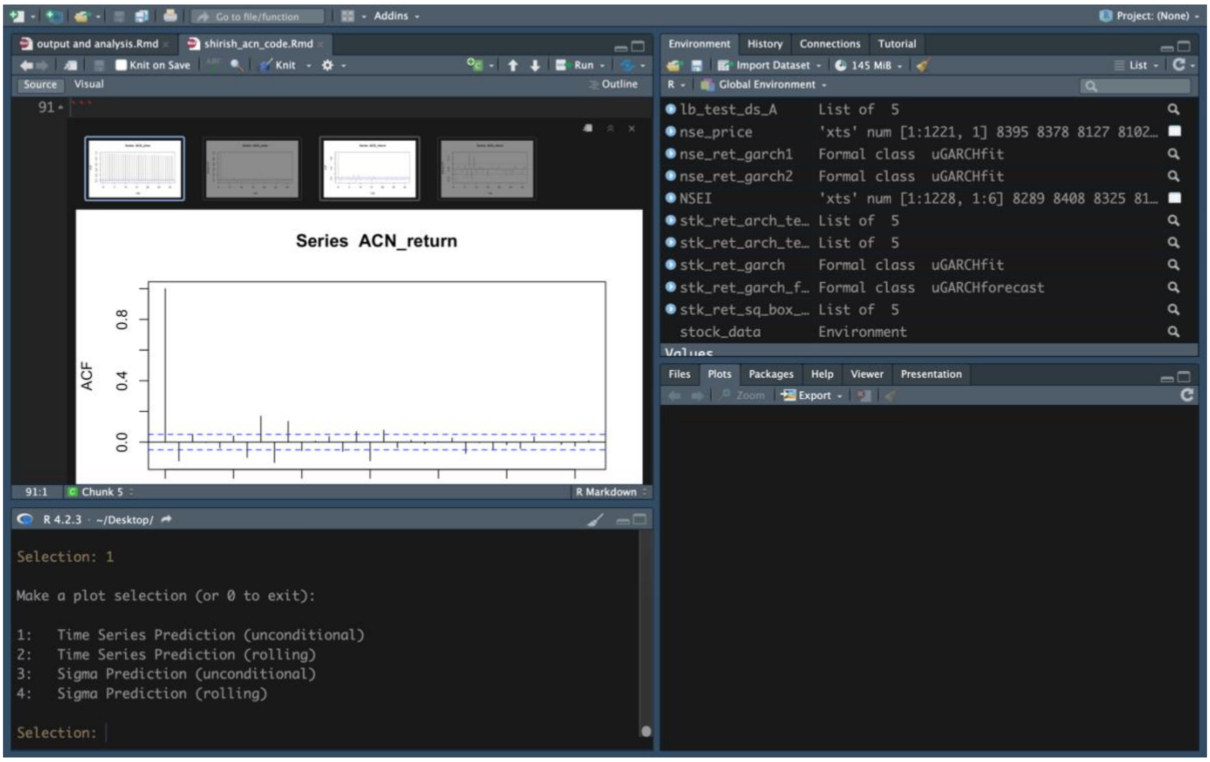
Action: Given the presence of autocorrelation, it may be advisable to consider an autoARIMA model for time series forecasting. AutoARIMA can help in automatically selecting an appropriate ARIMA model with differencing to account for the observed autocorrelation.



#ACF and PCF

```
acf(ACN_price) # ACF of JJ Series
pacf(ACN_price) # PACF of JJ Series

acf(ACN_return) # ACF of JJ Difference (Stationary) Series
pacf(ACN_return) # PACF of JJ Difference (Stationary) Series
```



Objective: To perform autoARIMA modeling on the daily returns ('ACN_return') and adjusted closing prices ('ACN_price') of accenture stock.
Analysis: Used the 'auto.arima' function to automatically select the ARIMA model for both returns and prices.
Results:
Series: ACN_return
ARIMA(1,0,0) with non-zero mean

```
Coefficients:
          ar1    mean
      -0.1224  6e-04
s.e.   0.0256  4e-04

sigma^2 = 0.000295:  log likelihood = 3990.04
AIC=-7974.07   AICc=-7974.06   BIC=-7958.12
```

Series: ACN_price
ARIMA(0,1,1)

```
Coefficients:
          ma1
      -0.0414
s.e.   0.0255

sigma^2 = 16.14:  log likelihood = -4236.27
AIC=8476.54   AICc=8476.55   BIC=8487.18
```

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

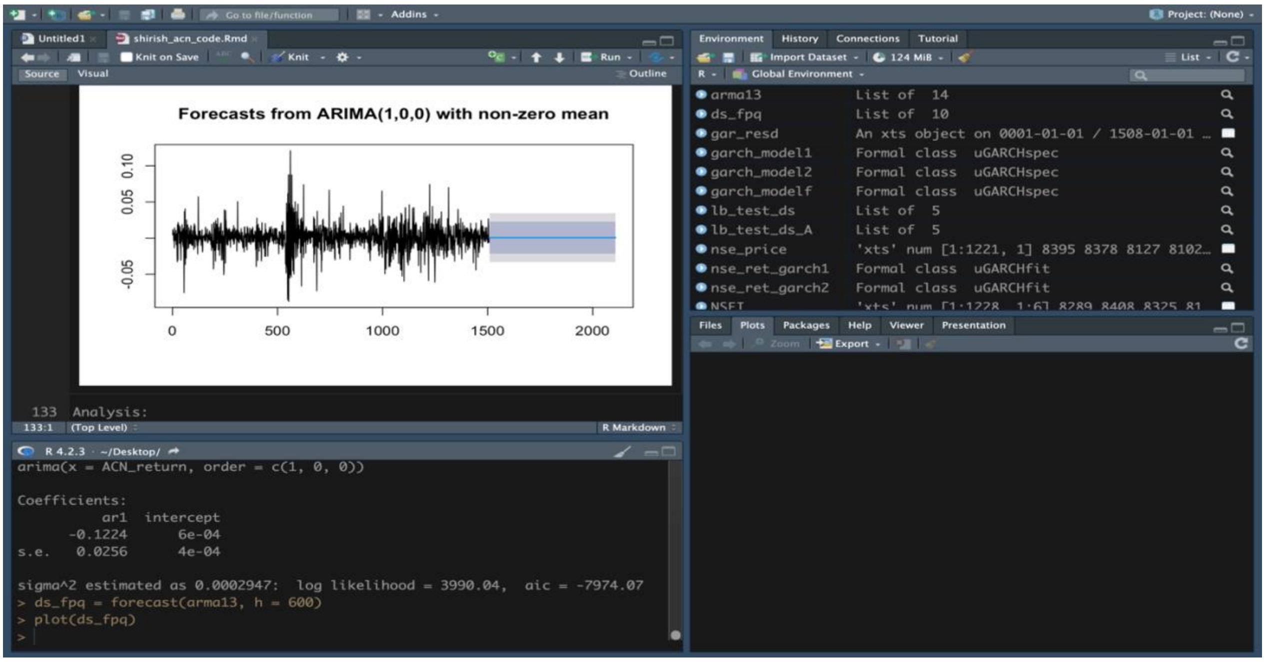
Objective: To fit an ARIMA(1, 0, 0) model to the daily returns ('ACN_return') of ITC stock and generate forecasts.
Analysis: Used the 'arima' function to fit the ARIMA model and the 'forecast' function to generate forecasts.
Results:

ARIMA Model (1, 0, 0):
coefficients:

```
        ar1  intercept
     -0.1224      6e-04
s.e.   0.0256      4e-04
```

sigma^2 estimated as 0.0002947: log likelihood = 3990.04, aic = -7974.07
Forecasting:
Generated forecasts for the next 600 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(1, 0, 0) model is fitted to the historical daily returns of Accenture 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.

Objective: To perform a Ljung-Box test for autocorrelation on the residuals of the ARIMA(1, 0, 0) 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:
Box-Pierce test
X-squared = 0.02497, df = 1, p-value = 0.8744
Implication:
The Ljung-Box test indicates no significant autocorrelation in the residuals of the ARIMA(1, 0, 0) model. The high p-value (0.8744) 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.

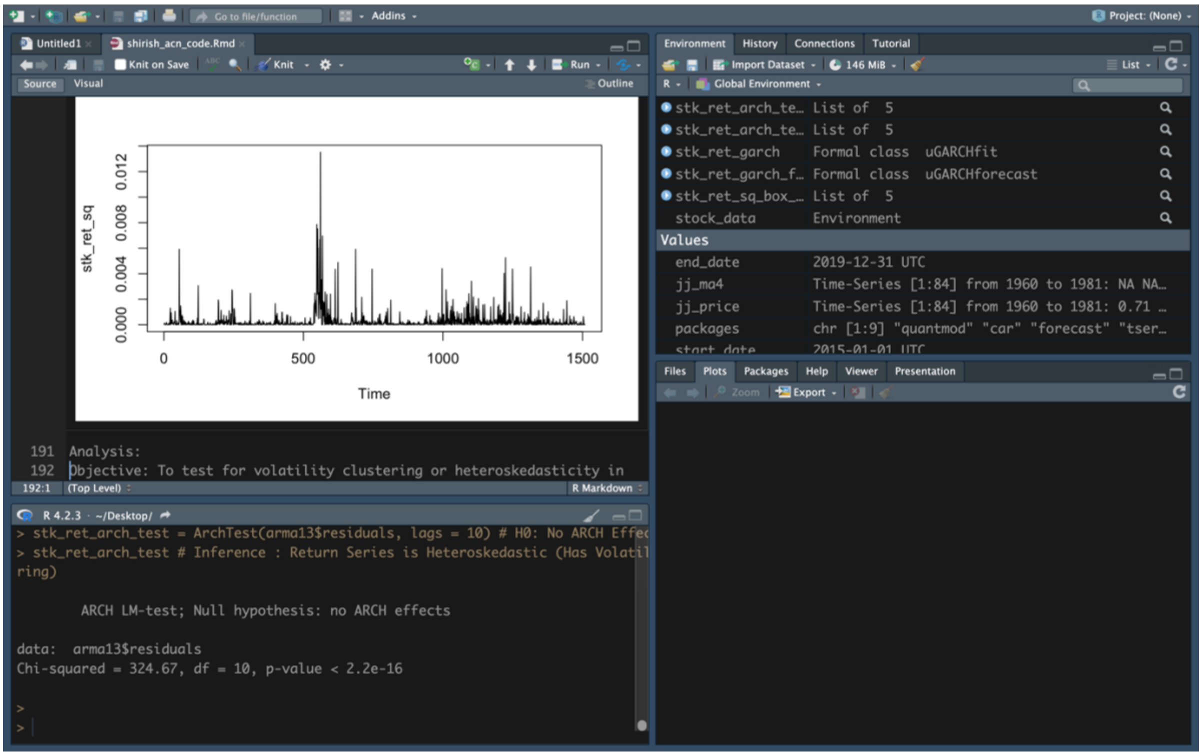
Note: Interpretation may vary based on the specific context of the financial data and the assumptions underlying the time series analysis.

Objective: To test for volatility clustering or heteroskedasticity in the residuals of the ARIMA(1, 0, 0) model.
Analysis: Conducted Box test and ARCH test on the squared residuals to assess the presence of volatility clustering.
Results:

data: stk_ret_sq
X-squared = 1013.9, df = 10, p-value < 2.2e-16

ARCH LM-test; Null hypothesis: no ARCH effects

data: arma13$residuals
Chi-squared = 324.67, 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. 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.



Objective: To fit GARCH models to the residuals of the ARIMA(1, 0, 0) 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: 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 0.000073 0.000348 0.20877 0.83463 omega 0.000013 0.000001 12.51770 0.00000 alpha1 0.159690 0.014078 11.34291 0.00000 beta1 0.804021 0.018556 43.32968 0.00000

Robust Standard Errors: Estimate Std. Error t value Pr(>|t|) mu 0.000073 0.000453 0.16018 0.87274 omega 0.000013 0.000002 7.25981 0.00000 alpha1 0.159690 0.026264 6.08019 0.00000 beta1 0.804021 0.032952 24.39958 0.00000

LogLikelihood : 4194.68

Information Criteria

Akaike -5.5579 Bayes -5.5438 Shibata -5.5579 Hannan-Quinn -5.5527

Weighted Ljung-Box Test on Standardized Residuals

statistic p-value

Lag[1] 13.02 0.0003078 Lag[2*(p+q)+(p+q)-1][2] 13.08 0.0002942 Lag[4*(p+q)+(p+q)-1][5] 13.18 0.0013598 d.o.f=0 H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

statistic p-value

Lag[1] 0.002693 0.9586 Lag[2*(p+q)+(p+q)-1][5] 0.579548 0.9447 Lag[4*(p+q)+(p+q)-1][9] 2.360103 0.8579 d.o.f=2

Weighted ARCH LM Tests

Statistic Shape Scale P-Value

ARCH Lag[3] 0.1044 0.500 2.000 0.7466 ARCH Lag[5] 0.5632 1.440 1.667 0.8648 ARCH Lag[7] 1.8264 2.315 1.543 0.7540

Nyblom stability test

Joint Statistic: 24.2682 Individual Statistics:

mu 3.04279 omega 2.21745 alpha1 0.06525 beta1 0.16816

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

Adjusted Pearson Goodness-of-Fit Test:

group statistic p-value(g-1) 1 20 75.34 1.165e-08 2 30 100.62 7.782e-10 3 40 102.82 1.178e-07 4 50 108.91 1.918e-06

Elapsed time : 0.5097089

———————————— * 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 -0.370654 0.024856 -14.912 0 ar2 0.734737 0.033039 22.238 0 ar3 -0.439821 0.027236 -16.148 0 ar4 -0.922278 0.014060 -65.594 0 ma1 0.496302 0.030257 16.403 0 ma2 -0.680113 0.030307 -22.441 0 ma3 0.362579 0.018322 19.789 0 ma4 0.967726 0.000426 2271.064 0 ma5 0.126279 0.017583 7.182 0 omega 0.000011 0.000001 11.918 0 alpha1 0.140998 0.012515 11.266 0 beta1 0.824651 0.016538 49.864 0

Robust Standard Errors: Estimate Std. Error t value Pr(>|t|) ar1 -0.370654 0.039017 -9.4998 0e+00 ar2 0.734737 0.057779 12.7163 0e+00 ar3 -0.439821 0.043861 -10.0275 0e+00 ar4 -0.922278 0.018712 -49.2868 0e+00 ma1 0.496302 0.045738 10.8511 0e+00 ma2 -0.680113 0.048030 -14.1601 0e+00 ma3 0.362579 0.032207 11.2579 0e+00 ma4 0.967726 0.000363 2663.7267 0e+00 ma5 0.126279 0.025777 4.8989 1e-06 omega 0.000011 0.000002 6.9892 0e+00 alpha1 0.140998 0.021538 6.5464 0e+00 beta1 0.824651 0.027745 29.7227 0e+00

LogLikelihood : 4208.72

Information Criteria

Akaike -5.5659 Bayes -5.5236 Shibata -5.5661 Hannan-Quinn -5.5502

Weighted Ljung-Box Test on Standardized Residuals

statistic p-value

Lag[1] 9.222e-04 0.9758 Lag[2*(p+q)+(p+q)-1][26] 7.792e+00 1.0000
Lag[4*(p+q)+(p+q)-1][44] 1.709e+01 0.9484 d.o.f=9 H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

statistic p-value

Lag[1] 0.0317 0.8587 Lag[2*(p+q)+(p+q)-1][5] 0.2136 0.9916
Lag[4*(p+q)+(p+q)-1][9] 1.7104 0.9366 d.o.f=2

Weighted ARCH LM Tests

Statistic Shape Scale P-Value

ARCH Lag[3] 0.05614 0.500 2.000 0.8127 ARCH Lag[5] 0.11857 1.440 1.667 0.9833 ARCH Lag[7] 1.25848 2.315 1.543 0.8682

Nyblom stability test

Joint Statistic: 25.3897 Individual Statistics:

ar1 0.12311 ar2 0.11636 ar3 0.07474 ar4 0.04386 ma1 0.10221 ma2 0.12468 ma3 0.07339 ma4 0.05557 ma5 0.21529 omega 2.15470 alpha1 0.05974 beta1 0.15615

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

Adjusted Pearson Goodness-of-Fit Test:

group statistic p-value(g-1) 1 20 75.08 1.292e-08 2 30 77.74 2.467e-06 3 40 98.31 5.016e-07 4 50 125.42 1.259e-08

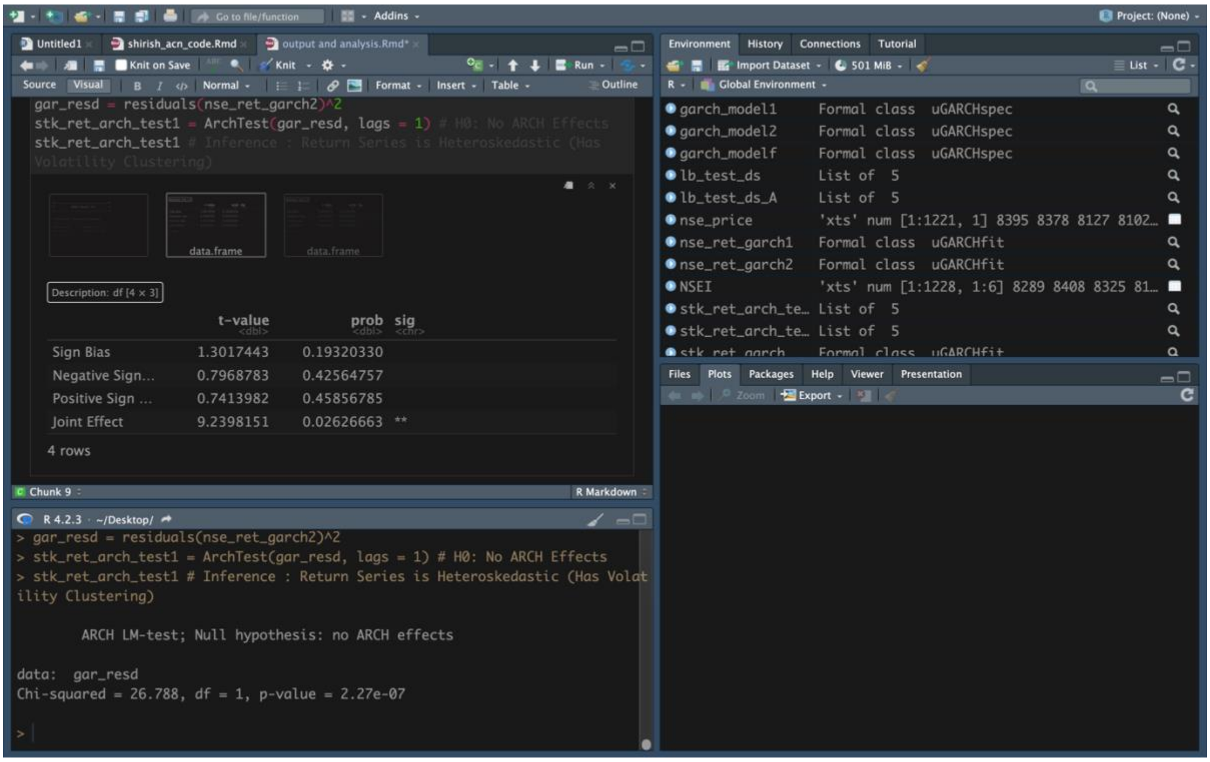
Elapsed time : 0.920485

ARCH LM-test; Null hypothesis: no ARCH effects

data: gar_resd Chi-squared = 31.031, df = 1, p-value = 2.539e-08

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.



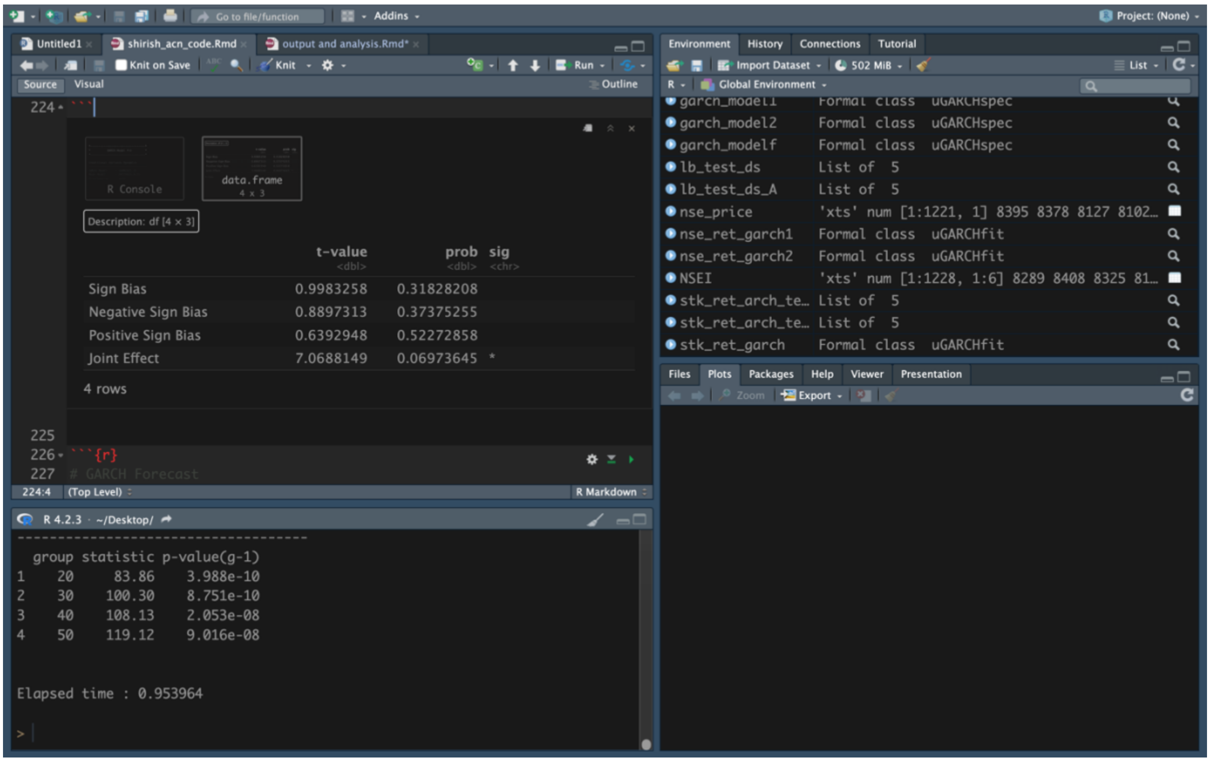
Objective: To fit a GARCH model to the daily returns of Accenture stock and assess the goodness-of-fit using the Adjusted Pearson Goodness-of-Fit Test.

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(1,0,0) 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., 2.314e-10), 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 Accenture 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.



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.