

Accenture Stock Time Series Analysis



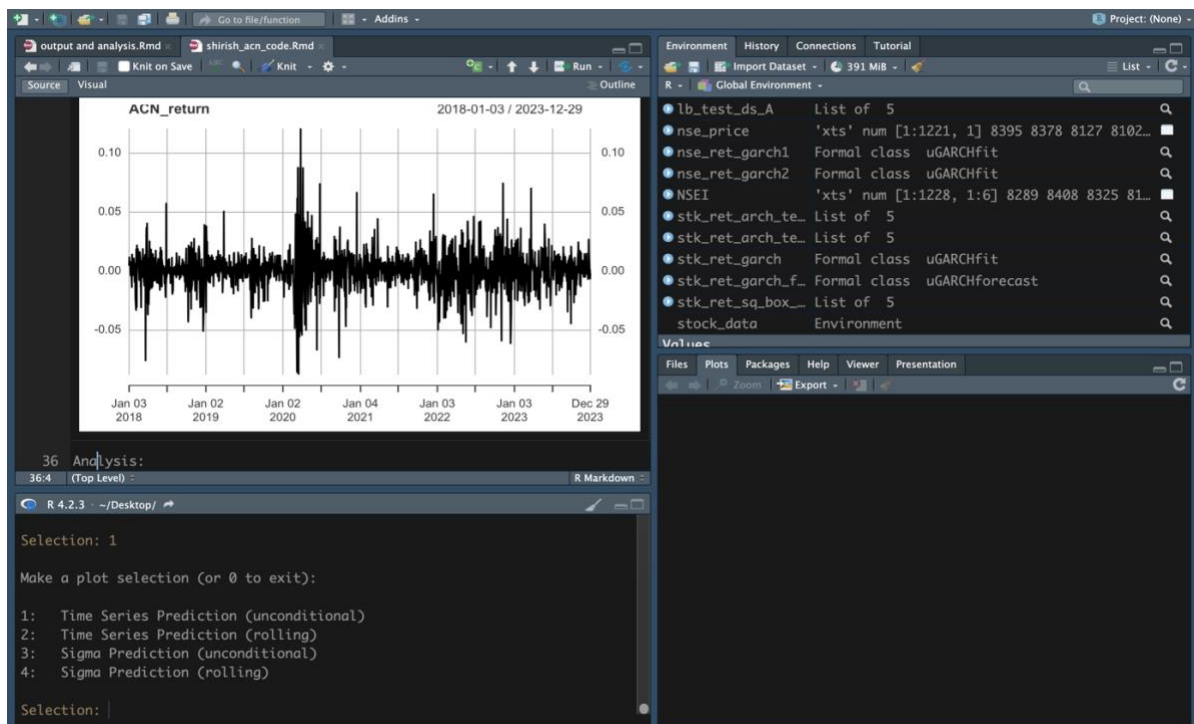
RTSM
MBA-BA

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Roll no: 35A

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.

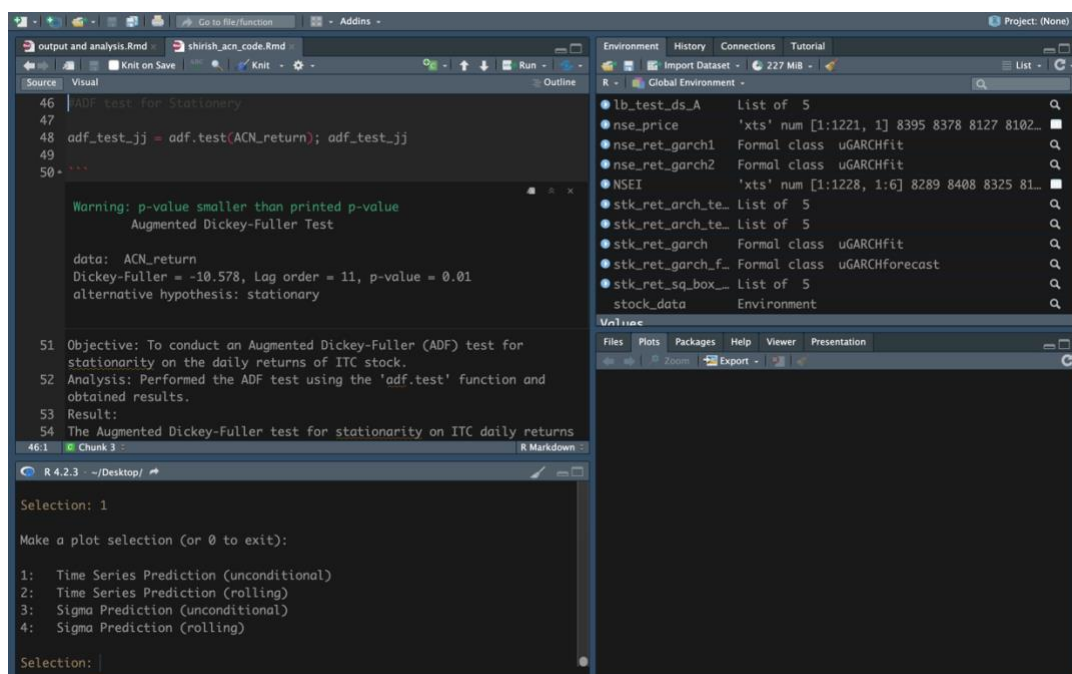
Result:

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.



```
46 | adf.test for Stationary
47 |
48 | adf_test_jj = adf.test(ACN_return); adf_test_jj
49 |
50 | ***
Warning: p-value smaller than printed p-value
Augmented Dickey-Fuller Test

data: ACN_return
Dickey-Fuller = -10.578, Lag order = 11, p-value = 0.01
alternative hypothesis: stationary

51 | Objective: To conduct an Augmented Dickey-Fuller (ADF) test for
52 | stationarity on the daily returns of ITC stock.
53 | Analysis: Performed the ADF test using the 'adf.test' function and
54 | obtained results.
55 | Result:
56 | The Augmented Dickey-Fuller test for stationarity on ITC daily returns

46:1 | Chunk 3:
R 4.2.3 ~/Desktop/
Selection: 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)
Selection: |
```

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.

The screenshot displays the RStudio interface. The main editor window shows R code for performing a Ljung-Box test on 'ACN_return' data. The code includes comments and function calls like `Box.test`. Below the code, a console window shows the output of the test: 'Box-Pierce test', 'data: ACN_return', 'X-squared = 22.606, df = 1, p-value = 1.989e-06'. The environment pane on the right lists various objects created during the session, including `lb_test_ds_A`, `nse_price`, `nse_ret_garch1`, `nse_ret_garch2`, `NSEI`, `stk_ret_arch_te`, `stk_ret_arch_te`, `stk_ret_garch`, `stk_ret_garch_f`, `stk_ret_sq_box`, and `stock_data`. The bottom pane shows a terminal window with a selection menu for time series prediction methods.

```
important for certain time series analyses.
62- ##{r}
63- #Autocorrelation test
64- # Ljung-Box Test for Autocorrelation
65- lb_test_ds = Box.test(ACN_return); lb_test_ds
66- #If autocorrelation exists then autoARIMA
67- ***
68- ***
```

Box-Pierce test

data: ACN_return
X-squared = 22.606, df = 1, p-value = 1.989e-06

```
69 Objective: To perform a Ljung-Box test for autocorrelation on the daily
70 returns of Accenture stock.
71 Analysis: Conducted the Ljung-Box test using the 'Box.test' function
and obtained results.
```

63:1 Chunk 4: R Markdown

R 4.2.3 ~./Desktop/

Selection: 1

Make a plot selection (or 0 to exit):

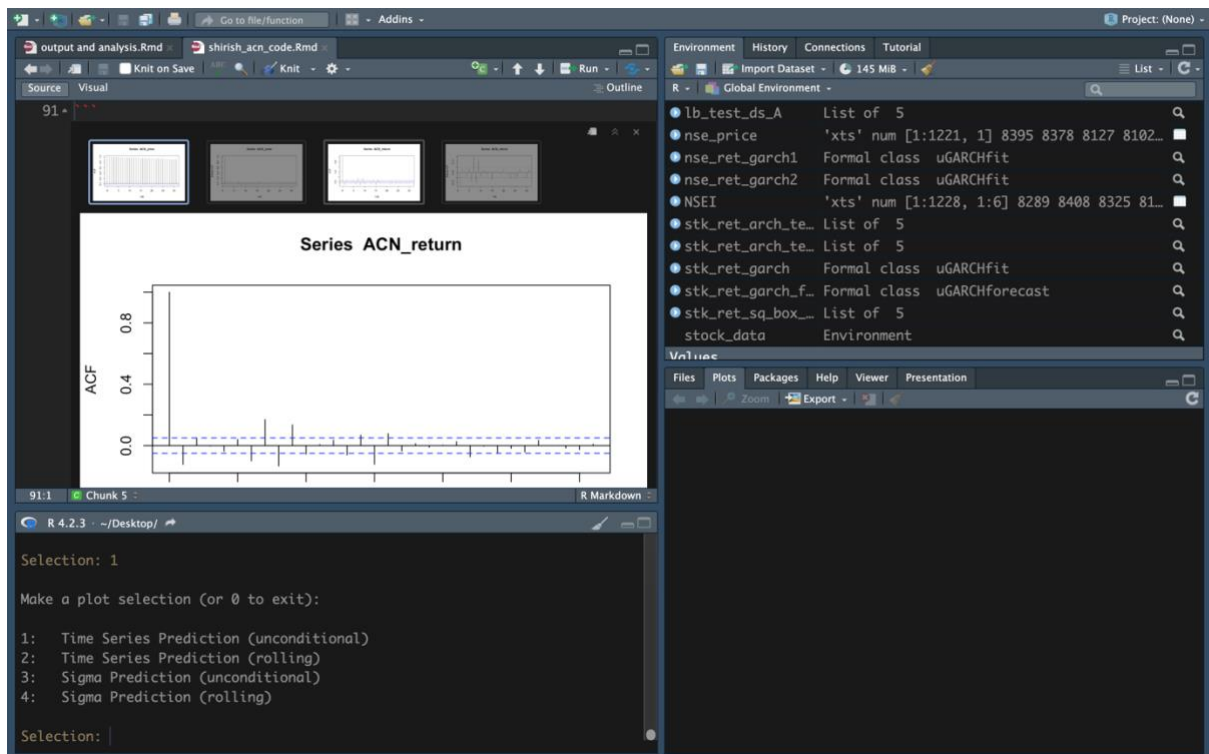
- 1: Time Series Prediction (unconditional)
- 2: Time Series Prediction (rolling)
- 3: Sigma Prediction (unconditional)
- 4: Sigma Prediction (rolling)

Selection: |

#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

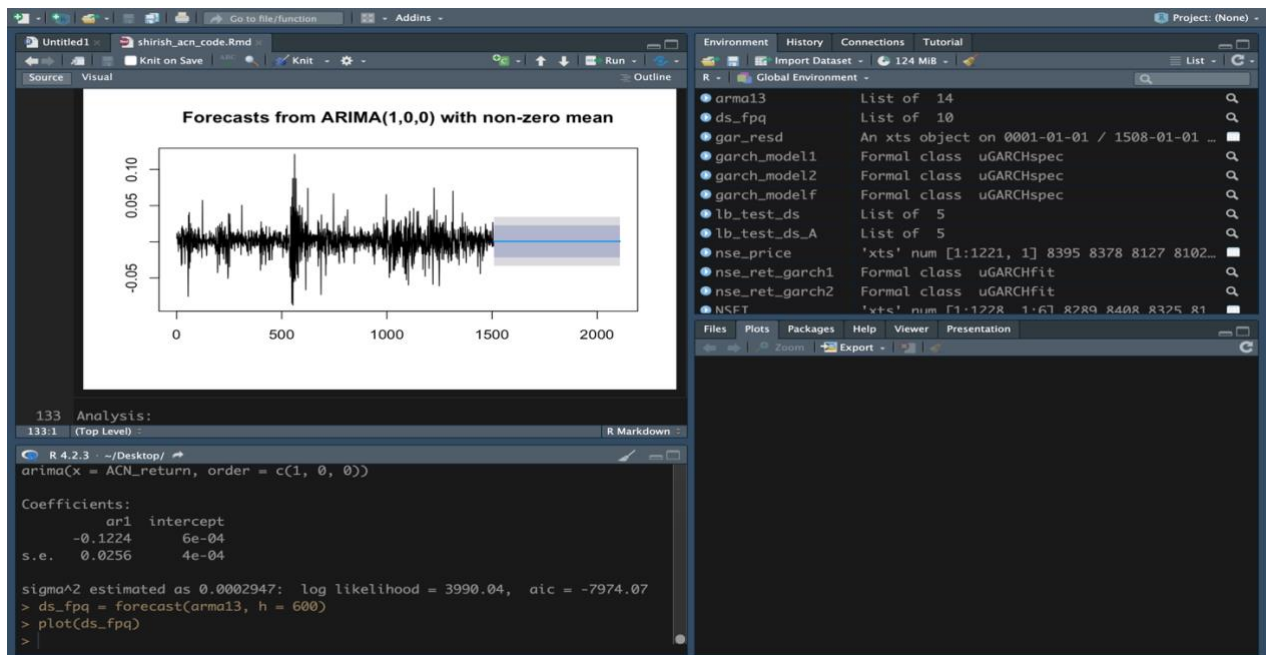
σ^2 estimated as 0.0002947: log likelihood = 3990.04, aic = -7974.07

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

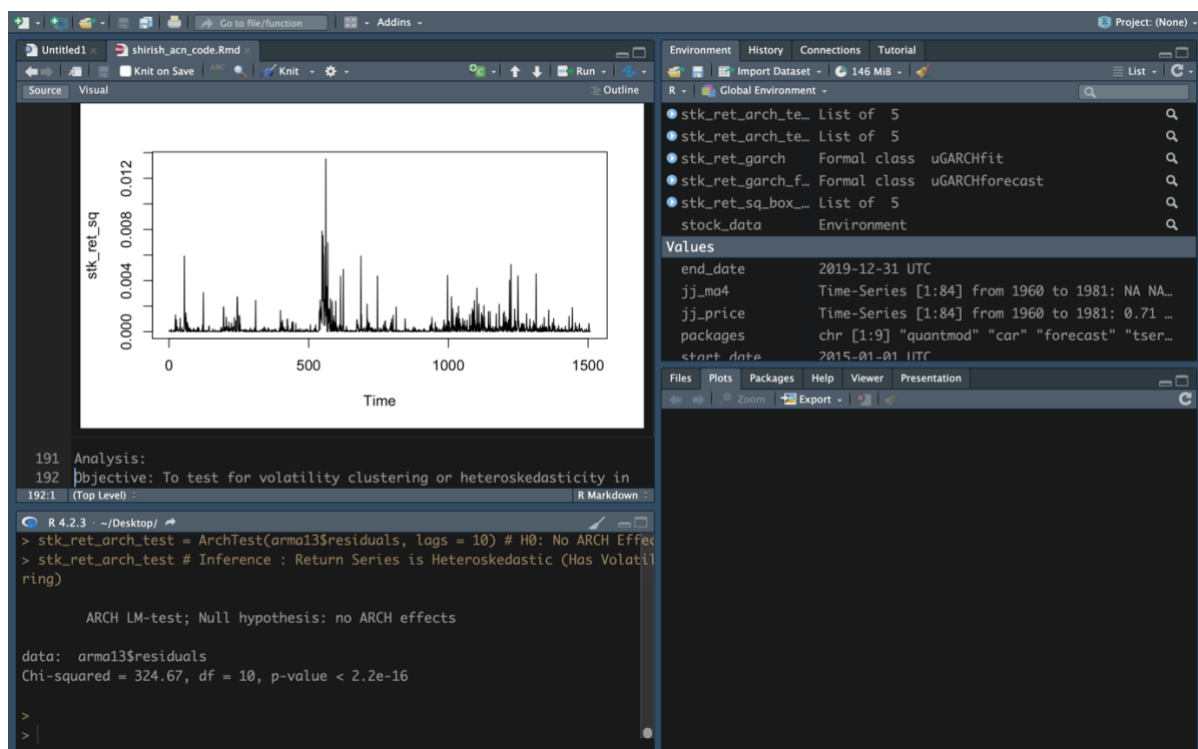
X-squared = 1013.9, df = 10, p-value < 2.2e-16

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
2	30	100.62
3	40	102.82
4	50	108.91

1.165e-08 1.178e-07 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

	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.

The screenshot displays the RStudio environment with the following components:

- Source Editor:** Contains R code for calculating residuals, performing an ARCH test, and an LM-test. The code includes comments and variable assignments.
- Environment Panel:** Lists objects in the global environment, including GARCH model specifications (garch_model1, garch_model2, garch_modelf), test results (lb_test_ds, lb_test_ds_A), and time series data (nse_price, nse_ret_garch1, nse_ret_garch2, NSEI).
- Console:** Shows the execution of the R code, including the results of the ARCH LM-test and the Chi-squared statistic.
- Viewer Panel:** Displays a table of test results for the Sign Bias test.

	t-value	prob	sig
Sign Bias	1.3017443	0.19320330	
Negative Sign...	0.7968783	0.42564757	
Positive Sign ...	0.7413982	0.45856785	
Joint Effect	9.2398151	0.02626663	**

4 rows

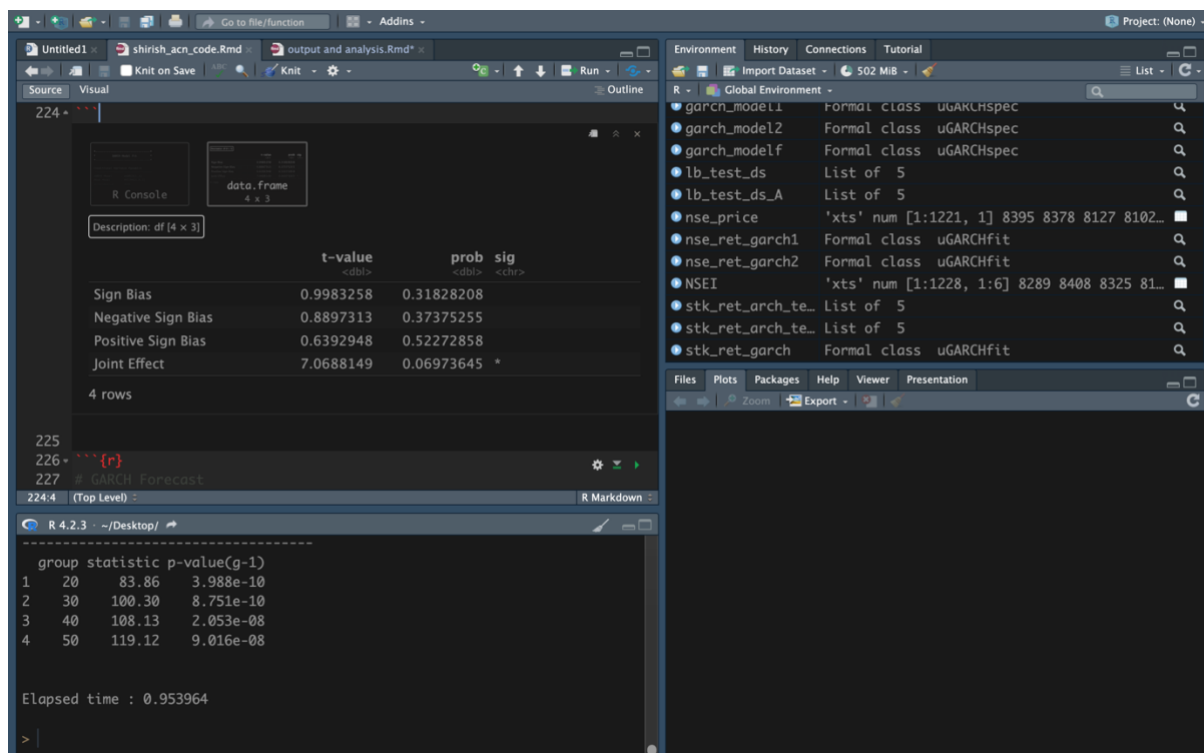
Objective: To fit a GARCH model to the daily returns of Accenture stock and assess the goodness-of-fit using the Adjusted Pearson Goodness-of-Fit Test.

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., 2.314×10^{-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.



The screenshot shows the RStudio interface with the following components:

- Source Editor:** Contains R code for fitting a GARCH model and performing the Adjusted Pearson Goodness-of-Fit Test.
- Environment Pane:** Lists the objects in the global environment, including `garch_model1`, `garch_model2`, `garch_model3`, `lb_test_ds`, `lb_test_ds_A`, `nse_price`, `nse_ret_garch1`, `nse_ret_garch2`, `NSEI`, `stk_ret_arch_te`, and `stk_ret_garch`.
- Console:** Displays the output of the test, showing a table of group sizes, statistics, and p-values.

group	statistic	p-value(g-1)
1 20	83.86	3.988×10^{-10}
2 30	100.30	8.751×10^{-10}
3 40	108.13	2.053×10^{-8}
4 50	119.12	9.016×10^{-8}

Elapsed time : 0.953964

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.

