

exercise3_109301060

May 14, 2024

1 Exercises for Lecture 3

109301060

1.0.1 Q1

a.

```
[ ]: import numpy as np
import pandas as pd
import statsmodels.formula.api as smf

data = pd.read_csv('data_exercise_3c.csv')
```

b.

```
[ ]: data['DATE'] = pd.to_datetime(data['DATE'])

# Calculate simple return
AAPL_sr = np.diff(data['AAPL_Adj_Close'])/data['AAPL_Adj_Close'][:-1]

data['AAPL_sr'] = np.append(np.nan, AAPL_sr)

# Calculate excess return
data['AAPL_rp'] = data['AAPL_sr'] - data['RF']
```

c.

```
[ ]: results_sst = data.loc[:, 'AAPL_sr': 'AAPL_rp'].describe()
print(results_sst)
```

| | AAPL_sr | AAPL_rp |
|-------|------------|------------|
| count | 130.000000 | 130.000000 |
| mean | 0.024280 | -0.017643 |
| std | 0.078486 | 0.102524 |
| min | -0.184045 | -0.364045 |
| 25% | -0.026441 | -0.074593 |
| 50% | 0.027021 | -0.011113 |
| 75% | 0.076592 | 0.060982 |
| max | 0.214380 | 0.204380 |

d.

```
[ ]: data = data.drop(data.index[0])

capm = smf.ols(formula = 'AAPL_rp ~ Mkt_RF', data = data)
result_capm = capm.fit()
print(f'result_capm.summary():\n{result_capm.summary()}\n')
```

```
result_capm.summary():
```

```

                        OLS Regression Results
=====
Dep. Variable:          AAPL_rp      R-squared:                0.239
Model:                  OLS          Adj. R-squared:            0.233
Method:                 Least Squares   F-statistic:            40.15
Date:                  Tue, 14 May 2024   Prob (F-statistic):      3.67e-09
Time:                  01:21:14         Log-Likelihood:          129.87
No. Observations:      130             AIC:                   -255.7
Df Residuals:          128             BIC:                   -250.0
Df Model:               1
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -0.0310      0.008     -3.801      0.000     -0.047     -0.015
Mkt_RF        0.0122      0.002      6.336      0.000      0.008      0.016
=====
Omnibus:              15.494   Durbin-Watson:           1.015
Prob(Omnibus):         0.000   Jarque-Bera (JB):        18.915
Skew:                 -0.712   Prob(JB):                7.81e-05
Kurtosis:              4.210   Cond. No.                 4.41
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

$$\alpha = -0.0310$$

$$\beta_{MKT} = 0.0122$$

e.

```
[ ]: ff3 = smf.ols(formula = 'AAPL_rp ~ Mkt_RF + SMB + HML', data = data)
result_ff3 = ff3.fit()
print(f'result_ff3.summary():\n{result_ff3.summary()}\n')
```

```
result_ff3.summary():
```

```

                        OLS Regression Results
=====
```

```

Dep. Variable:          AAPL_rp    R-squared:                0.255
Model:                  OLS        Adj. R-squared:           0.237
Method:                 Least Squares    F-statistic:             14.37
Date:                  Tue, 14 May 2024    Prob (F-statistic):      4.13e-08
Time:                  01:21:14    Log-Likelihood:          131.26
No. Observations:      130        AIC:                     -254.5
Df Residuals:          126        BIC:                     -243.1
Df Model:               3
Covariance Type:       nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -0.0329      0.008     -4.008      0.000     -0.049     -0.017
Mkt_RF        0.0134      0.002      6.458      0.000      0.009      0.018
SMB          -0.0047      0.003     -1.377      0.171     -0.011      0.002
HML          -0.0013      0.003     -0.490      0.625     -0.006      0.004
=====

```

```

Omnibus:            18.784    Durbin-Watson:           0.959
Prob(Omnibus):      0.000    Jarque-Bera (JB):        24.644
Skew:               -0.802    Prob(JB):                4.45e-06
Kurtosis:           4.406    Cond. No.                4.65
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

$$\alpha = -0.0329$$

$$\beta_{MKT} = 0.0134$$

$$\beta_{SMB} = -0.0047$$

$$\beta_{HML} = -0.0013$$

f.

```

[ ]: ff5 = smf.ols(formula = 'AAPL_rp ~ Mkt_RF + SMB + HML + RMW + CMA', data = data)
      result_ff5 = ff5.fit()
      print(f'result_ff5.summary():\n{result_ff5.summary()}\n')

```

result_ff5.summary():

```

              OLS Regression Results
=====
Dep. Variable:          AAPL_rp    R-squared:                0.307
Model:                  OLS        Adj. R-squared:           0.279
Method:                 Least Squares    F-statistic:             10.98
Date:                  Tue, 14 May 2024    Prob (F-statistic):      9.20e-09
Time:                  01:21:15    Log-Likelihood:          135.96
No. Observations:      130        AIC:                     -259.9

```

Df Residuals: 124 BIC: -242.7
Df Model: 5
Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|-------------------|----------|-------|--------|--------|
| Intercept | -0.0348 | 0.008 | -4.300 | 0.000 | -0.051 | -0.019 |
| Mkt_RF | 0.0122 | 0.002 | 5.724 | 0.000 | 0.008 | 0.016 |
| SMB | 0.0006 | 0.004 | 0.160 | 0.873 | -0.007 | 0.008 |
| HML | -0.0018 | 0.003 | -0.562 | 0.575 | -0.008 | 0.005 |
| RMW | 0.0140 | 0.005 | 3.011 | 0.003 | 0.005 | 0.023 |
| CMA | -0.0034 | 0.006 | -0.606 | 0.545 | -0.015 | 0.008 |
| Omnibus: | 16.992 | Durbin-Watson: | 0.951 | | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 21.040 | | | |
| Skew: | -0.766 | Prob(JB): | 2.70e-05 | | | |
| Kurtosis: | 4.239 | Cond. No. | 4.78 | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

$$\alpha = -0.0348$$

$$\beta_{MKT} = 0.0122$$

$$\beta_{SMB} = 0.0006$$

$$\beta_{HML} = -0.0018$$

$$\beta_{RMW} = 0.0140$$

$$\beta_{CMA} = -0.0034$$

g.

```
[ ]: ff6 = smf.ols(formula = 'AAPL_rp ~ Mkt_RF + SMB + HML + RMW + CMA + MOM', data_
      ↪= data)
result_ff6 = ff6.fit()
print(f'result_ff6.summary():\n{result_ff6.summary()}\n')
```

result_ff6.summary():

| OLS Regression Results | | | |
|------------------------|------------------|---------------------|----------|
| Dep. Variable: | AAPL_rp | R-squared: | 0.312 |
| Model: | OLS | Adj. R-squared: | 0.279 |
| Method: | Least Squares | F-statistic: | 9.309 |
| Date: | Tue, 14 May 2024 | Prob (F-statistic): | 2.08e-08 |
| Time: | 01:21:15 | Log-Likelihood: | 136.47 |

No. Observations: 130 AIC: -258.9
Df Residuals: 123 BIC: -238.9
Df Model: 6
Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|-------------------|----------|-------|--------|--------|
| Intercept | -0.0358 | 0.008 | -4.391 | 0.000 | -0.052 | -0.020 |
| Mkt_RF | 0.0128 | 0.002 | 5.771 | 0.000 | 0.008 | 0.017 |
| SMB | 0.0012 | 0.004 | 0.314 | 0.754 | -0.006 | 0.009 |
| HML | -0.0005 | 0.004 | -0.156 | 0.876 | -0.008 | 0.006 |
| RMW | 0.0146 | 0.005 | 3.117 | 0.002 | 0.005 | 0.024 |
| CMA | -0.0037 | 0.006 | -0.651 | 0.516 | -0.015 | 0.008 |
| MOM | 0.0027 | 0.003 | 0.989 | 0.325 | -0.003 | 0.008 |
| Omnibus: | 15.389 | Durbin-Watson: | 0.958 | | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 18.536 | | | |
| Skew: | -0.716 | Prob(JB): | 9.44e-05 | | | |
| Kurtosis: | 4.170 | Cond. No. | 5.32 | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

$$\alpha = -0.0358$$

$$\beta_{MKT} = 0.0128$$

$$\beta_{SMB} = 0.0012$$

$$\beta_{HML} = -0.005$$

$$\beta_{RMW} = 0.0146$$

$$\beta_{CMA} = -0.0037$$

$$\beta_{MOM} = 0.0027$$

h.

```
[ ]: capm_alpha = round(result_capm.params['Intercept'], 4)
ff3_alpha = round(result_ff3.params['Intercept'], 4)
ff5_alpha = round(result_ff5.params['Intercept'], 4)
ff6_alpha = round(result_ff6.params['Intercept'], 4)

print('CAPM Alpha :', capm_alpha)
print('FF3 Alpha :', ff3_alpha)
print('FF5 Alpha :', ff5_alpha)
print('FF6 Alpha :', ff6_alpha)
```

CAPM Alpha : -0.031
FF3 Alpha : -0.0329
FF5 Alpha : -0.0348
FF6 Alpha : -0.0358

α α α

1.0.2 Q2

a.

```
[ ]: import wooldridge as woo
import numpy as np
import statsmodels.formula.api as smf

wage2 = woo.data('WAGE2')

reg_IQ = smf.ols(formula = 'IQ ~ educ', data = wage2)
results_IQ = reg_IQ.fit()
delta_educ_hat = results_IQ.params['educ']

print(round(results_IQ.params, 4))
```

Intercept 53.6872
educ 3.5338
dtype: float64

b.

```
[ ]: reg1 = smf.ols(formula = 'np.log(wage) ~ educ', data = wage2)
results1 = reg1.fit()
beta_educ_tilde = results1.params['educ']

print(round(results1.params, 4))
```

Intercept 5.9731
educ 0.0598
dtype: float64

c.

```
[ ]: reg = smf.ols(formula = 'np.log(wage) ~ educ + IQ', data = wage2)
results = reg.fit()
beta_hat = results.params

print(beta_hat)
```

Intercept 5.658288
educ 0.039120
IQ 0.005863
dtype: float64

d.

```
[ ]: print('Value by regression:', beta_educ_tilde)
      beta_educ_tilde1 = beta_hat['educ'] + beta_hat['IQ'] * delta_educ_hat
      print('Value by equation :', round(beta_educ_tilde1, 4))
```

Value by regression: 0.05983920788637073

Value by equation : 0.0598

e.

```
[ ]: delta_int_hat = results_IQ.params['Intercept']
      beta_int_tilde = results1.params['Intercept']
      print('Value by regression:', beta_int_tilde)

      beta_int_tilde1 = results.params['Intercept'] + results.
        ↪ params['IQ'] * delta_int_hat
      print('Value by equation :', round(beta_int_tilde1, 4))
```

Value by regression: 5.973062450264955

Value by equation : 5.9731

1.0.3 Q3

```
[ ]: import statsmodels.api as sm
      import numpy as np
      import statsmodels.formula.api as smf

      # Redo the OLS estimation
      wage1 = woo.data('wage1')

      reg = smf.ols(formula='np.log(wage) ~ educ + exper + tenure', data = wage1)
      results = reg.fit()
      beta_educ_hat = results.params['educ']
      beta_educ_hat = round(beta_educ_hat, 4)

      print(f'beta_educ_hat: \n{beta_educ_hat}')

      # The first step: regress educ on exper and tenure with the OLS
      # and save the residuals
      reg_educ = smf.ols(formula='educ ~ exper + tenure', data = wage1)
      results_educ = reg_educ.fit()
      wage1['resid_educ'] = results_educ.resid

      # The second step: regress log(wage) on resid_educ with the OLS
      # and obtain the estimated slop parameter
      reg1 = smf.ols(formula='np.log(wage) ~ resid_educ', data = wage1)
      results1 = reg1.fit()
      beta_educ_hat1 = results1.params['resid_educ']
```

```

beta_educ_hat1 = round(beta_educ_hat1, 4)

print(f'beta_educ_hat1: \n{beta_educ_hat1}')

# Is this result applied to the estimated intercept?
# The first step: regress a vector of ones on educ, exper and tenure with the
↳ OLS
# and save the residuals
# note that NO INTERCEPT HERE!
wage1['ones'] = 1 # add a vector of ones into the data set
reg_int = smf.ols(formula='ones ~ educ + exper + tenure -1', data = wage1)
results_int = reg_int.fit()
wage1['resid_int'] = results_int.resid

# The second step: regress y on resid_educ with the OLS
# and obtain the estimated slop parameter
reg_int1 = smf.ols(formula='np.log(wage) ~ resid_int', data = wage1)
results_int1 = reg_int1.fit()
beta_int_hat1 = results_int1.params['resid_int']
beta_int_hat1 = round(beta_int_hat1, 4)

# The OLS intercept from original regression
beta_int_hat = results.params['Intercept']
beta_int_hat = round(beta_int_hat, 4)

print(f'beta_int_hat: \n{beta_int_hat}')
print(f'beta_int_hat1: \n{beta_int_hat1}')

```

```

beta_educ_hat:
0.092
beta_educ_hat1:
0.092
beta_int_hat:
0.2844
beta_int_hat1:
-1.3861

```

\hat{r}_1 and β_1 is the same, but the result not applied to estimating the intercept term β_0 .