homework6_2023

March 9, 2023

Chapter 8 Problems: 3, 8

3A) Analysts following A = -0.2845 + 0.3199(log(100)) + -0.1895(0.75) + e = 1.0465689425 Analysts following B = -0.2845 + 0.3199(log(1,000)) + -0.1895(0.75) + e = 1.78316591375

1.78316591375-1.0465689425=0.73659697125 Analysts

3B) A p-value is the probability of a nonzero correlation coefficient when the null hypothesis is true. A p-value of 0.00236 for D/E ratio would suggest that there is a very low chance of the data happening in the null hypothesis, therefore we should reject the null hypothesis and accept the alternative hypothesis that this coefficient is valid.

Python exercise

Compare the performance of the following two mutual funds using CAPM and multi-factor models: Fidelity Magellan, ticker: FMGKX Vanguard 500 Index Fund, ticker:VFINX

[1]:
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
from pandas_datareader import data as pdr
```

[2]:
```
mm=pdr.DataReader('F-F_Momentum_Factor_daily','famafrench',
                  start='1991-1-1')[0]
```

Read in three factors (market, size, book to market) from Professor French's website as a dataframe

[3]:
```
from pandas_datareader.famafrench import get_available_datasets
get_available_datasets()
```

[3]:
```
['F-F_Research_Data_Factors',
 'F-F_Research_Data_Factors_weekly',
 'F-F_Research_Data_Factors_daily',
 'F-F_Research_Data_5_Factors_2x3',
 'F-F_Research_Data_5_Factors_2x3_daily',
 'Portfolios_Formed_on_ME',
 'Portfolios_Formed_on_ME_Wout_Div',
 'Portfolios_Formed_on_ME_Daily',
 'Portfolios_Formed_on_BE-ME',
 'Portfolios_Formed_on_BE-ME_Wout_Div',
 'Portfolios_Formed_on_BE-ME_Daily',
```

```
'Portfolios_Formed_on_OP',
'Portfolios_Formed_on_OP_Wout_Div',
'Portfolios_Formed_on_OP_Daily',
'Portfolios_Formed_on_INV',
'Portfolios_Formed_on_INV_Wout_Div',
'Portfolios_Formed_on_INV_Daily',
'6_Portfolios_2x3',
'6_Portfolios_2x3_Wout_Div',
'6_Portfolios_2x3_weekly',
'6_Portfolios_2x3_daily',
'25_Portfolios_5x5',
'25_Portfolios_5x5_Wout_Div',
'25_Portfolios_5x5_Daily',
'100_Portfolios_10x10',
'100_Portfolios_10x10_Wout_Div',
'100_Portfolios_10x10_Daily',
'6_Portfolios_ME_OP_2x3',
'6_Portfolios_ME_OP_2x3_Wout_Div',
'6_Portfolios_ME_OP_2x3_daily',
'25_Portfolios_ME_OP_5x5',
'25_Portfolios_ME_OP_5x5_Wout_Div',
'25_Portfolios_ME_OP_5x5_daily',
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'100_Portfolios_10x10_ME_OP_Wout_Div',
'100_Portfolios_ME_OP_10x10_daily',
'6_Portfolios_ME_INV_2x3',
'6_Portfolios_ME_INV_2x3_Wout_Div',
'6_Portfolios_ME_INV_2x3_daily',
'25_Portfolios_ME_INV_5x5',
'25_Portfolios_ME_INV_5x5_Wout_Div',
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'100_Portfolios_ME_INV_10x10_daily',
'25_Portfolios_BEME_OP_5x5',
'25_Portfolios_BEME_OP_5x5_Wout_Div',
'25_Portfolios_BEME_OP_5x5_daily',
'25_Portfolios_BEME_INV_5x5',
'25_Portfolios_BEME_INV_5x5_Wout_Div',
'25_Portfolios_BEME_INV_5x5_daily',
'25_Portfolios_OP_INV_5x5',
'25_Portfolios_OP_INV_5x5_Wout_Div',
'25_Portfolios_OP_INV_5x5_daily',
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'32_Portfolios_ME_BEME_OP_2x4x4_Wout_Div',
'32_Portfolios_ME_BEME_INV_2x4x4',
'32_Portfolios_ME_BEME_INV_2x4x4_Wout_Div',
```

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'Portfolios_Formed_on_E-P_Wout_Div',
'Portfolios_Formed_on_CF-P',
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'Portfolios_Formed_on_D-P',
'Portfolios_Formed_on_D-P_Wout_Div',
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'10_Portfolios_Prior_12_2_Daily',
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'F-F_ST_Reversal_Factor_daily',
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'Developed_25_Portfolios_ME_OP_Daily',
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'Europe_25_Portfolios_ME_OP_Daily',
'Japan_25_Portfolios_ME_OP',
'Japan_25_Portfolios_ME_OP_Daily',
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'Asia_Pacific_ex_Japan_6_Portfolios_ME_INV_Daily',
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'Japan_25_Portfolios_ME_INV_Daily',
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'North_America_25_Portfolios_ME_INV_Daily',
```

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'Developed_ex_US_6_Portfolios_ME_Prior_250_20_daily',
'Europe_6_Portfolios_ME_Prior_12_2',
'Europe_6_Portfolios_ME_Prior_250_20_daily',
'Japan_6_Portfolios_ME_Prior_12_2',
'Japan_6_Portfolios_ME_Prior_250_20_daily',
'Asia_Pacific_ex_Japan_6_Portfolios_ME_Prior_12_2',
'Asia_Pacific_ex_Japan_6_Portfolios_ME_Prior_250_20_daily',
'North_America_6_Portfolios_ME_Prior_12_2',
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'Developed_ex_US_25_Portfolios_ME_Prior_12_2',
'Developed_ex_US_25_Portfolios_ME_Prior_250_20_daily',
'Europe_25_Portfolios_ME_Prior_12_2',
'Europe_25_Portfolios_ME_Prior_250_20_daily',
'Japan_25_Portfolios_ME_Prior_12_2',
'Japan_25_Portfolios_ME_Prior_250_20_daily',
'Asia_Pacific_ex_Japan_25_Portfolios_ME_Prior_12_2',
'Asia_Pacific_ex_Japan_25_Portfolios_ME_Prior_250_20_daily',
'North_America_25_Portfolios_ME_Prior_12_2',
'North_America_25_Portfolios_ME_Prior_250_20_daily',
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'Developed_ex_US_32_Portfolios_ME_BE-ME_OP_2x4x4',
'Europe_32_Portfolios_ME_BE-ME_OP_2x4x4',
'Japan_32_Portfolios_ME_BE-ME_OP_2x4x4',
'Asia_Pacific_ex_Japan_32_Portfolios_ME_BE-ME_OP_2x4x4',
'North_America_32_Portfolios_ME_BE-ME_OP_2x4x4',
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'Europe_32_Portfolios_ME_BE-ME_INV(TA)_2x4x4',
'Japan_32_Portfolios_ME_BE-ME_INV(TA)_2x4x4',
'Asia_Pacific_ex_Japan_32_Portfolios_ME_BE-ME_INV(TA)_2x4x4',
'North_America_32_Portfolios_ME_BE-ME_INV(TA)_2x4x4',
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'Japan_32_Portfolios_ME_INV(TA)_OP_2x4x4',
'Asia_Pacific_ex_Japan_32_Portfolios_ME_INV(TA)_OP_2x4x4',
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'Emerging_MOM_Factor',
'Emerging_Markets_6_Portfolios_ME_BE-ME',
'Emerging_Markets_6_Portfolios_ME_OP',
'Emerging_Markets_6_Portfolios_ME_INV',
```

```
 'Emerging_Markets_6_Portfolios_ME_Prior_12_2',
 'Emerging_Markets_4_Portfolios_BE-ME_OP',
 'Emerging_Markets_4_Portfolios_OP_INV',
 'Emerging_Markets_4_Portfolios_BE-ME_INV']
```

[4]:
```python
ff=pdr.
 ↪DataReader('F-F_Research_Data_Factors_daily','famafrench',start='1991-1-1')[0]
ff.head()
```

[4]:
```
            Mkt-RF   SMB   HML     RF
Date
1991-01-02   -0.95  0.64  0.82  0.023
1991-01-03   -1.25  0.28  1.17  0.023
1991-01-04   -0.24  0.12  0.42  0.023
1991-01-07   -1.72  0.32  0.23  0.023
1991-01-08   -0.29 -0.36 -0.01  0.023
```

Read in adjusted close price for both funds from Yahoo finance. Use the earliest date possible when data are available for both funds

[5]:
```python
import yfinance as yf
yf.pdr_override()
```

[6]:
```python
tickers=['FMGKX','VFINX']

sec_data=pd.DataFrame()

for t in tickers:
    sec_data[t]=pdr.get_data_yahoo(t,start='2000-1-1')['Adj Close']
```

```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
```

[7]:
```python
sec_data.head()
```

[7]:
```
               FMGKX      VFINX
Date
2008-05-09  3.767782  96.915611
2008-05-12  3.804223  97.990494
2008-05-13  3.804223  97.975365
2008-05-14  3.817831  98.384132
2008-05-15  3.874468  99.443871
```

Calculate the simple daily returns using Adj. Close

[8]:
```python
sec_returns=(sec_data/sec_data.shift(1)-1)*100
sec_returns.head()
```

[8]:

```
                FMGKX     VFINX
Date
2008-05-09        NaN       NaN
2008-05-12  0.967176  1.109091
2008-05-13  0.000000 -0.015439
2008-05-14  0.357713  0.417215
2008-05-15  1.483475  1.077143
```

Merge the factors with stock returns

[9]:

```
all=pd.merge(sec_returns,ff,left_index=True,right_index=True)
all=all.dropna()
all.head()
```

[9]:

```
                FMGKX     VFINX  Mkt-RF   SMB   HML     RF
Date
2008-05-12  0.967176  1.109091    1.10  0.69 -0.40  0.008
2008-05-13  0.000000 -0.015439    0.09  0.66 -0.14  0.008
2008-05-14  0.357713  0.417215    0.38 -0.41  0.11  0.008
2008-05-15  1.483475  1.077143    1.02 -0.10 -0.32  0.008
2008-05-16  0.679897  0.129428    0.10 -0.41 -0.02  0.008
```

Calculate excess mutual fund returns (fund return-rf)

[10]:

```
all['FMGKX-RF']=all['FMGKX']-all['RF']
all['VFINX-RF']=all['VFINX']-all['RF']
all.head()
```

[10]:

```
                FMGKX     VFINX  Mkt-RF   SMB   HML     RF  FMGKX-RF  VFINX-RF
Date
2008-05-12  0.967176  1.109091    1.10  0.69 -0.40  0.008  0.959176  1.101091
2008-05-13  0.000000 -0.015439    0.09  0.66 -0.14  0.008 -0.008000 -0.023439
2008-05-14  0.357713  0.417215    0.38 -0.41  0.11  0.008  0.349713  0.409215
2008-05-15  1.483475  1.077143    1.02 -0.10 -0.32  0.008  1.475475  1.069143
2008-05-16  0.679897  0.129428    0.10 -0.41 -0.02  0.008  0.671897  0.121428
```

Run a CAPM model to evaluate performance of the two funds (use excess return as the dependent variable)

[11]:

```
X=all['Mkt-RF']
```

[12]:

```
X1=sm.add_constant(X)

reg_FMGKX=sm.OLS(all['FMGKX-RF'],X1).fit()
reg_VFINX=sm.OLS(all['VFINX-RF'],X1).fit()
```

[13]:

```
reg_FMGKX.summary()
```

[13]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               FMGKX-RF   R-squared:                       0.951
Model:                            OLS   Adj. R-squared:                  0.951
Method:                 Least Squares   F-statistic:                 7.161e+04
Date:                Thu, 09 Mar 2023   Prob (F-statistic):               0.00
Time:                        22:15:08   Log-Likelihood:                -1060.1
No. Observations:                3707   AIC:                             2124.
Df Residuals:                    3705   BIC:                             2137.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0086      0.005     -1.617      0.106      -0.019       0.002
Mkt-RF         1.0660      0.004    267.596      0.000       1.058       1.074
==============================================================================
Omnibus:                      509.851   Durbin-Watson:                   1.865
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5152.766
Skew:                          -0.292   Prob(JB):                         0.00
Kurtosis:                       8.746   Cond. No.                         1.33
==============================================================================

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

[14]:
```
reg_VFINX.summary()
```

[14]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               VFINX-RF   R-squared:                       0.993
Model:                            OLS   Adj. R-squared:                  0.993
Method:                 Least Squares   F-statistic:                 5.224e+05
Date:                Thu, 09 Mar 2023   Prob (F-statistic):               0.00
Time:                        22:15:08   Log-Likelihood:                 2916.9
No. Observations:                3707   AIC:                            -5830.
Df Residuals:                    3705   BIC:                            -5817.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
```

```
------------------------------------------------------------------------------
const         -0.0003      0.002     -0.147      0.883      -0.004       0.003
Mkt-RF         0.9848      0.001    722.765      0.000       0.982       0.987
==============================================================================
Omnibus:                      709.586   Durbin-Watson:                   2.070
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9924.825
Skew:                           0.497   Prob(JB):                         0.00
Kurtosis:                      10.954   Cond. No.                         1.33
==============================================================================

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

Based on the CAPM, which fund has higher systematic risk?

Based on the CAPM, FMGKX has higher systematic risk since it's coefficient is higher.

Based on the CAPM, did Magellan perform better/worse than the market?

Based on the CAPM, FMGKX performed better than the market.

Based on the CAPM, what proportion of Magellan fund's risk is systematic risk?

[ ]:
```
risk_proportion=1.0660/0.004
risk_proportion
```

Run a Fama-French three-factor model to evaluate performance of the two funds (use excess return as the dependent variable)

[28]:
```
#double bracket to reference list of variables all[[list]]
X=all[['Mkt-RF','SMB','HML']]
X.head()
```

[28]:
```
            Mkt-RF   SMB   HML
Date
2008-05-12    1.10  0.69 -0.40
2008-05-13    0.09  0.66 -0.14
2008-05-14    0.38 -0.41  0.11
2008-05-15    1.02 -0.10 -0.32
2008-05-16    0.10 -0.41 -0.02
```

[29]:
```
X1=sm.add_constant(X)

reg_FMGKX=sm.OLS(all['FMGKX-RF'],X1).fit()
reg_VFINX=sm.OLS(all['VFINX-RF'],X1).fit()
```

[30]:
```
reg_FMGKX.summary()
```

[30]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               FMGKX-RF   R-squared:                       0.961
Model:                            OLS   Adj. R-squared:                  0.961
Method:                 Least Squares   F-statistic:                 3.031e+04
Date:                Thu, 09 Mar 2023   Prob (F-statistic):               0.00
Time:                        22:19:38   Log-Likelihood:                -636.02
No. Observations:                3707   AIC:                             1280.
Df Residuals:                    3703   BIC:                             1305.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0097      0.005     -2.052      0.040      -0.019      -0.000
Mkt-RF         1.0944      0.004    296.918      0.000       1.087       1.102
SMB           -0.0890      0.007    -11.881      0.000      -0.104      -0.074
HML           -0.1614      0.005    -29.516      0.000      -0.172      -0.151
==============================================================================
Omnibus:                      459.237   Durbin-Watson:                   1.902
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5073.104
Skew:                          -0.041   Prob(JB):                         0.00
Kurtosis:                       8.730   Cond. No.                         2.17
==============================================================================

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

[31]:
```
reg_VFINX.summary()
```

[31]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               VFINX-RF   R-squared:                       0.998
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                 5.052e+05
Date:                Thu, 09 Mar 2023   Prob (F-statistic):               0.00
Time:                        22:19:39   Log-Likelihood:                 4883.7
No. Observations:                3707   AIC:                            -9759.
Df Residuals:                    3703   BIC:                            -9735.
Df Model:                           3
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8.073e-05      0.001      0.076      0.940      -0.002       0.002
Mkt-RF         0.9932      0.001   1194.410      0.000       0.992       0.995
SMB           -0.1366      0.002    -80.834      0.000      -0.140      -0.133
HML            0.0165      0.001     13.392      0.000       0.014       0.019
==============================================================================
Omnibus:                      552.007   Durbin-Watson:                   2.066
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7839.424
Skew:                           0.179   Prob(JB):                         0.00
Kurtosis:                      10.115   Cond. No.                         2.17
==============================================================================

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

How do we interpret the regression coefficient for the size factor and the coefficient for the book to market factor?

The size factor regression coefficient is SMB, which is the tendency for small companies to outperform big ones. Both FMGKX and VFINX having a negative coefficient tells us that both funds behave more similarly to a big company rather than a small company.

The book to market factor regression coefficient is HML, which states the high minus low market to book factor. This coefficient suggest that FMGKX behaves like a value stock and VFINX doesn't act like either.

Based on the three-facor model, did Magellan perform better/worse than the market?

Based on the three-factor model, Magelllan performed slightly better than the market since FMGKX-RF>1.

Based on the three-facor model, did Vanguard 500 Index fund perform better/worse than the market?

Based on the three-factor model, Vanguard 500 performed slightly worse than the market since VFINX-RF<1.

Optional challenge: Evaluate the performance of Magellan using the Fama-French-Carhart 4-factor model.