

Econometrics_HW2_2.10

September 7, 2019

1 Question 2.10

1.1 A) The econometric model $r_j - r_f = \alpha(j) + \beta(j) * (r_m - r_f) + e$ is a simple regression model as the equation represents a straight line which has a y- intercept and a slope component. Here, the y-intercept component is alpha which is the expected excess return and beta is a slope which is a risk factor and implies the effect of change in risk premium on returns.

1.2 B) Here we are estimating the CAPM Model for each of the 6 firms and analyzing the estimated beta values

```
[17]: #importing libraries
```

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
%matplotlib inline
```

```
[18]: #Checking current working directory
```

```
import os
os.chdir("C:\\Users\\nishc\\Downloads")
```

```
[19]: #Loading data set
```

```
data= pd.read_stata("capm4.dta")
data.head()
```

```
[19]:
```

	date	dis	ge	gm	ibm	msft	xom	\
0	19980130	0.080884	0.056218	-0.046296	-0.056153	0.154255	-0.030644	
1	19980227	0.047368	0.003226	0.198490	0.059620	0.136154	0.081728	
2	19980331	-0.046343	0.112379	-0.017226	-0.005386	0.056047	0.060784	
3	19980430	0.168337	-0.011603	-0.005535	0.115523	0.006983	0.080407	
4	19980529	-0.090818	-0.021277	0.074212	0.015922	-0.058946	-0.029461	

	mkt	riskfree
0	0.004529	0.004188
1	0.073230	0.004268
2	0.051322	0.004358

```
3  0.010862  0.003940
4 -0.025755  0.003806
```

```
[20]: #checking for NaN values in the Dataset
data.isnull().sum()
```

```
[20]: date      0
dis      0
ge      0
gm      0
ibm     0
msft    0
xom     0
mkt     0
riskfree 0
dtype: int64
```

```
[21]: #Risk Premium for Market Portfolio

RP_mkt= data["mkt"]-data["riskfree"]

# Risk Premium for each Stocks
RP_dis= data["dis"]- data["riskfree"]
RP_ge= data["ge"]- data["riskfree"]
RP_gm= data["gm"]- data["riskfree"]
RP_ibm= data["ibm"]- data["riskfree"]
RP_msft= data["msft"]- data["riskfree"]
RP_xom= data["xom"]- data["riskfree"]
```

```
[22]: #CAPM Models

x= sm.add_constant(RP_mkt)

#CAPM Model for Disney

model1= sm.OLS(RP_dis,x)
result1=model1.fit()
print(result1.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.289
Model:                  OLS    Adj. R-squared:       0.283
Method:                 Least Squares    F-statistic:      52.74
Date:                   Sat, 07 Sep 2019    Prob (F-statistic): 3.11e-11
Time:                   14:26:07    Log-Likelihood:    167.72
```

```

No. Observations:      132    AIC:                -331.4
Df Residuals:          130    BIC:                -325.7
Df Model:              1
Covariance Type:      nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const         -0.0011      0.006      -0.193      0.847      -0.013      0.011
0              0.8978      0.124       7.262      0.000       0.653      1.142
=====

Omnibus:                15.249    Durbin-Watson:           2.426
Prob(Omnibus):           0.000    Jarque-Bera (JB):        25.331
Skew:                    0.546    Prob(JB):                3.16e-06
Kurtosis:                 4.847    Cond. No.                 20.8
=====

```

Warnings:

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

C:\Users\nishc\AppData\Local\Continuum\anaconda3\lib\site-packages\numpy\core\fromnumeric.py:2389: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
return ptp(axis=axis, out=out, **kwargs)

1.2.1 The Beta value of Disney's Stock is 0.8978. Therefore, we can say that the stock is DEFENSIVE

```

[23]: #CAPM Model for GE

model2= sm.OLS(RP_ge,x)
result2=model2.fit()
print(result2.summary())

```

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                0.389
Model:                          OLS      Adj. R-squared:           0.385
Method:                        Least Squares      F-statistic:             82.87
Date:                          Sat, 07 Sep 2019      Prob (F-statistic):       1.33e-15
Time:                          14:26:07      Log-Likelihood:          197.34
No. Observations:              132      AIC:                    -390.7
Df Residuals:                  130      BIC:                    -384.9
Df Model:                      1
Covariance Type:              nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----

```

```

const      -0.0012      0.005      -0.245      0.807      -0.011      0.008
0           0.8993      0.099       9.104      0.000      0.704      1.095
=====
Omnibus:                3.287      Durbin-Watson:                2.239
Prob(Omnibus):          0.193      Jarque-Bera (JB):            2.872
Skew:                   0.238      Prob(JB):                    0.238
Kurtosis:               3.544      Cond. No.                    20.8
=====

```

Warnings:

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

1.2.2 The Beta value of GE's Stock is 0.8993. Therefore, we can say that the stock is DEFENSIVE

```

[24]: #CAPM Model for GM

model3= sm.OLS(RP_gm,x)
result3=model3.fit()
print(result3.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:                0.230
Model:                  OLS      Adj. R-squared:            0.224
Method:                 Least Squares      F-statistic:            38.91
Date:                  Sat, 07 Sep 2019      Prob (F-statistic):      5.77e-09
Time:                  14:26:08      Log-Likelihood:          102.76
No. Observations:      132      AIC:                     -201.5
Df Residuals:          130      BIC:                     -195.8
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0116	0.010	-1.185	0.238	-0.031	0.008
0	1.2614	0.202	6.238	0.000	0.861	1.661

```

=====
Omnibus:                4.443      Durbin-Watson:                2.063
Prob(Omnibus):          0.108      Jarque-Bera (JB):            4.999
Skew:                   -0.187      Prob(JB):                    0.0821
Kurtosis:               3.877      Cond. No.                    20.8
=====

```

Warnings:

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

1.2.3 The Beta value of GM's Stock is 1.2614. Therefore, we can say that the stock is AGGRESSIVE

[25]: *#CAPM Model for IBM*

```
model4= sm.OLS(RP_ibm,x)
result4=model4.fit()
print(result4.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                0.405
Model:                        OLS      Adj. R-squared:           0.400
Method:                    Least Squares   F-statistic:                88.32
Date:                Sat, 07 Sep 2019   Prob (F-statistic):       2.52e-16
Time:                14:26:08   Log-Likelihood:           164.76
No. Observations:          132   AIC:                      -325.5
Df Residuals:              130   BIC:                      -319.8
Df Model:                   1
Covariance Type:            nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0059      0.006      0.961      0.339      -0.006      0.018
0              1.1882      0.126      9.398      0.000       0.938      1.438
=====
Omnibus:                 19.729   Durbin-Watson:           2.172
Prob(Omnibus):            0.000   Jarque-Bera (JB):         61.477
Skew:                    0.439   Prob(JB):                 4.47e-14
Kurtosis:                6.226   Cond. No.                  20.8
=====

```

Warnings:

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

1.2.4 The Beta value of IBM's Stock is 1.1882. Therefore, we can say that the stock is AGGRESSIVE

[26]: *#CAPM Model for Microsoft*

```
model5= sm.OLS(RP_msft,x)
result5=model5.fit()
print(result5.summary())
```

```
NameError                                Traceback (most recent call
↳last)
```

```
<ipython-input-26-08abe29001ef> in <module>
      3 model5= sm.OLS(RP_msft,x)
      4 result5=model5.fit()
----> 5 print(result.summary())
```

```
NameError: name 'result' is not defined
```

1.2.5 The Beta value of Microsoft's Stock is 1.3189. Therefore, we can say that the stock is AGGRESSIVE

[27]: *#CAPM Model for Exxon Mobil*

```
model6= sm.OLS(RP_xom,x)
result6=model6.fit()
print(result6.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.141
Model:                  OLS    Adj. R-squared:      0.134
Method:                 Least Squares  F-statistic:      21.29
Date:                   Sat, 07 Sep 2019  Prob (F-statistic):  9.33e-06
Time:                   14:26:09  Log-Likelihood:      210.05
No. Observations:      132      AIC:              -416.1
Df Residuals:          130      BIC:              -410.3
Df Model:               1
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0079	0.004	1.823	0.071	-0.001	0.016
0	0.4140	0.090	4.614	0.000	0.236	0.591

```
=====
Omnibus:                22.128  Durbin-Watson:          2.348
Prob(Omnibus):          0.000  Jarque-Bera (JB):        40.767
Skew:                   0.747  Prob(JB):                1.40e-09
Kurtosis:               5.276  Cond. No.                20.8
=====
```

Warnings:

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

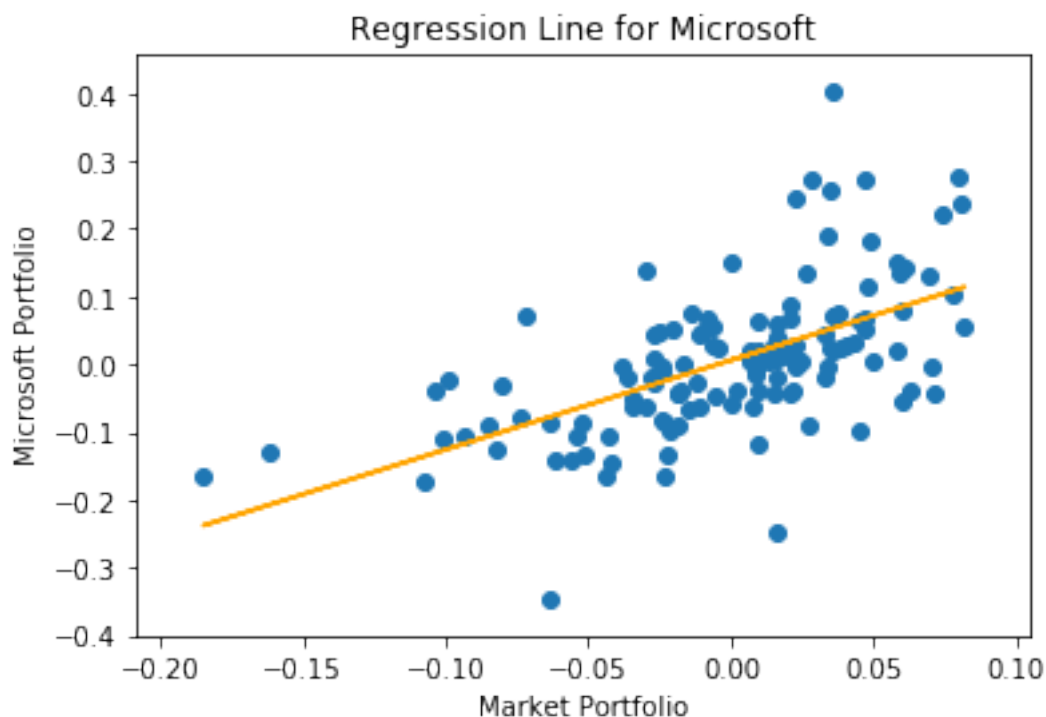
1.2.6 The Beta value of Exxon Mobil's Stock is 0.414. Therefore, we can say that the stock is DEFENSIVE

1.3 From the above analysis of the beta values of different value it is seen that Exxon Mobil has the lowest and most defensive beta value which is 0.4140. Whereas, IBM has the highest and most aggressive beta value which is 1.8820

1.4 C) The obtained alpha values are very close to Zero as stated by the Finance Theory. Thus, the theory seems to be correct as per the given datesets.

1.4.1 Fitted Regression line of Microsoft across the scatter plot

```
[37]: plt.scatter(RP_mkt, RP_msft)
plt.plot(RP_mkt,result5.predict(x), color='orange')
plt.xlabel("Market Portfolio")
plt.ylabel(" Microsoft Portfolio")
plt.title("Regression Line for Microsoft")
plt.show()
```



1.5 Estimating CAPM Model for $\alpha=0$

```
[38]: x1= RP_mkt + np.zeros(132)
```

```
[39]: #CAPM Model for Disney
```

```

model11= sm.OLS(RP_dis,x1)
result11=model11.fit()
print(result11.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          y    R-squared (uncentered):
0.289
Model:                OLS    Adj. R-squared (uncentered):
0.283
Method:              Least Squares    F-statistic:
53.14
Date:                Sat, 07 Sep 2019    Prob (F-statistic):
2.62e-11
Time:                14:32:14    Log-Likelihood:
167.70
No. Observations:    132    AIC:
-333.4
Df Residuals:        131    BIC:
-330.5
Df Model:              1
Covariance Type:      nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
x1	0.8979	0.123	7.290	0.000	0.654	1.142

```

=====
Omnibus:              15.250    Durbin-Watson:              2.426
Prob(Omnibus):        0.000    Jarque-Bera (JB):          25.332
Skew:                 0.547    Prob(JB):                  3.16e-06
Kurtosis:             4.847    Cond. No.:                  1.00
=====

```

Warnings:

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

[40]: *#CAPM Model for GE*

```

model22= sm.OLS(RP_ge,x1)
result22=model22.fit()
print(result22.summary())

```

OLS Regression Results

```

=====
=====

```



```

Dep. Variable:                y    R-squared (uncentered):
0.389
Model:                        OLS    Adj. R-squared (uncentered):
0.385
Method:                        Least Squares    F-statistic:
83.49
Date:                          Sat, 07 Sep 2019    Prob (F-statistic):
1.04e-15
Time:                          14:32:14    Log-Likelihood:
197.31
No. Observations:              132    AIC:
-392.6
Df Residuals:                  131    BIC:
-389.7
Df Model:                      1
Covariance Type:               nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
x1	0.8993	0.098	9.137	0.000	0.705	1.094

```

=====
Omnibus:                      3.287    Durbin-Watson:                2.238
Prob(Omnibus):                 0.193    Jarque-Bera (JB):              2.873
Skew:                          0.238    Prob(JB):                      0.238
Kurtosis:                     3.544    Cond. No.                      1.00
=====

```

Warnings:

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

[41]: *#CAPM Model for GM*

```

model33= sm.OLS(RP_gm,x1)
result33=model33.fit()
print(result33.summary())

```

OLS Regression Results

```

=====
Dep. Variable:                y    R-squared (uncentered):
0.229
Model:                        OLS    Adj. R-squared (uncentered):
0.223
Method:                        Least Squares    F-statistic:
38.84
Date:                          Sat, 07 Sep 2019    Prob (F-statistic):

```

```

5.84e-09
Time:                  14:32:14   Log-Likelihood:
102.05
No. Observations:      132   AIC:
-202.1
Df Residuals:          131   BIC:
-199.2
Df Model:              1
Covariance Type:      nonrobust
=====
              coef    std err          t      P>|t|      [0.025      0.975]
-----
x1              1.2622     0.203     6.232     0.000     0.862     1.663
=====
Omnibus:            4.446   Durbin-Watson:           2.041
Prob(Omnibus):      0.108   Jarque-Bera (JB):           5.004
Skew:              -0.187   Prob(JB):              0.0819
Kurtosis:           3.878   Cond. No.              1.00
=====

```

Warnings:

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

[42]: *#CAPM Model for IBM*

```

model44= sm.OLS(RP_ibm,x1)
result44=model44.fit()
print(result44.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          y   R-squared (uncentered):
0.403
Model:                OLS   Adj. R-squared (uncentered):
0.398
Method:              Least Squares   F-statistic:
88.31
Date:                Sat, 07 Sep 2019   Prob (F-statistic):
2.38e-16
Time:                14:32:14   Log-Likelihood:
164.29
No. Observations:      132   AIC:
-326.6
Df Residuals:          131   BIC:
-323.7

```

```

Df Model: 1
Covariance Type: nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
x1              1.1878      0.126      9.398      0.000      0.938      1.438
=====
Omnibus: 19.736    Durbin-Watson: 2.157
Prob(Omnibus): 0.000    Jarque-Bera (JB): 61.502
Skew: 0.439    Prob(JB): 4.41e-14
Kurtosis: 6.227    Cond. No. 1.00
=====

```

Warnings:

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

[43]: *#CAPM Model for Microsoft*

```

model55= sm.OLS(RP_msft,x1)
result55=model55.fit()
print(result55.summary())

```

OLS Regression Results

```

=====
Dep. Variable: y    R-squared (uncentered): 0.340
Model: OLS    Adj. R-squared (uncentered): 0.335
Method: Least Squares    F-statistic: 67.44
Date: Sat, 07 Sep 2019    Prob (F-statistic): 1.81e-13
Time: 14:32:14    Log-Likelihood: 132.71
No. Observations: 132    AIC: -263.4
Df Residuals: 131    BIC: -260.5
Df Model: 1
Covariance Type: nonrobust
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
x1              1.3185      0.161      8.212      0.000      1.001      1.636
=====

```

Omnibus:	16.074	Durbin-Watson:	2.334
Prob(Omnibus):	0.000	Jarque-Bera (JB):	34.121
Skew:	0.473	Prob(JB):	3.90e-08
Kurtosis:	5.304	Cond. No.	1.00

=====

Warnings:

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

[44]: *#CAPM Model for Exxon-Mobil*

```
model66= sm.OLS(RP_xom,x1)
result66=model66.fit()
print(result66.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          y    R-squared (uncentered):
0.137
Model:                  OLS    Adj. R-squared (uncentered):
0.131
Method:                 Least Squares    F-statistic:
20.87
Date:                   Sat, 07 Sep 2019    Prob (F-statistic):
1.12e-05
Time:                   14:32:15    Log-Likelihood:
208.38
No. Observations:       132    AIC:
-414.8
Df Residuals:           131    BIC:
-411.9
Df Model:                1
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
x1	0.4134	0.091	4.568	0.000	0.234	0.592

```
=====
Omnibus:                22.136    Durbin-Watson:           2.290
Prob(Omnibus):           0.000    Jarque-Bera (JB):        40.789
Skew:                    0.747    Prob(JB):                1.39e-09
Kurtosis:                5.277    Cond. No.:               1.00
=====
```

Warnings:

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

1.6 Difference in beta values when $\alpha=1$ and $\alpha=0$

```
[45]: diff1= result11.params[0]-result1.params[0]
diff2= result22.params[0]-result2.params[0]
diff3= result33.params[0]-result3.params[0]
diff4= result44.params[0]-result4.params[0]
diff5= result55.params[0]-result5.params[0]
diff6= result66.params[0]-result6.params[0]

print(" The Difference in beta value of Disney when alpha=0 is", diff1)
print(" The Difference in beta value of GE when alpha=0 is", diff2)
print(" The Difference in beta value of GM when alpha=0 is", diff3)
print(" The Difference in beta value of IBM when alpha=0 is", diff4)
print(" The Difference in beta value of Microsoft when alpha=0 is", diff5)
print(" The Difference in beta value of Exxon-Mobil when alpha=0 is", diff6)
```

```
The Difference in beta value of Disney when alpha=0 is 8.118574049187366e-05
The Difference in beta value of GE when alpha=0 is 8.242353869281072e-05
The Difference in beta value of GM when alpha=0 is 0.0008158078392714874
The Difference in beta value of IBM when alpha=0 is -0.00041328961773245965
The Difference in beta value of Microsoft when alpha=0 is
-0.0004306836658243274
The Difference in beta value of Exxon-Mobil when alpha=0 is
-0.0005565950793665619
```

1.7 D) As we can observe from the results that there is a negligible difference in the beta values.