

Yifu-He-Homework6

May 13, 2020

```
In [1]: import pandas as pd
import numpy as np
import os
```

1 Question 1

```
In [4]: path = "/Users/yifuhe/Learning/RBS/fin_model/homework6"
HXZ_factor = pd.read_excel(path+"/Data_q_factors.xlsx")
five_factor = pd.read_excel(path+"/F-F_Research_Data_5_Factors_2x3.xlsx")
fama_french = pd.read_excel(path+"/F-F_Research_Data_Factors.xlsx")
# read data from path
port_25 = pd.read_excel(path+"/25_Portfolios_5x5.xlsx")
# 25 Fama-French size and book to market sorted portfolios
colname = port_25.iloc[14,:].values
colname[0] = "Date"
data = port_25.iloc[15:-2,:].reset_index().drop("index",axis = 1)
data.columns = colname
for i in range(len(data["Date"])):
    if not isinstance(data["Date"][i],(int,float)):
        print(i,data.Date[i])
#data["Date"] = pd.to_datetime(data.loc["Date"].apply(str),format = "%Y%m")
```

```
1126 Average Equal Weighted Returns -- Monthly
2254 Average Value Weighted Returns -- Annual
2351 Average Equal Weighted Returns -- Annual
2448 Number of Firms in Portfolios
3576 Average Market Cap
4704 For portfolios formed in June of year t
4705 Value Weight Average of BE/ME Calculated for June of t to June of t+1 as:
4706 Sum[ME(Mth) * BE(Fiscal Year t-1) / ME(Dec t-1)] / Sum[ME(Mth)]
4707 Where Mth is a month from June of t to June of t+1
4708 and BE(Fiscal Year t-1) is adjusted for net stock issuance to Dec t-1
5836 For portfolios formed in June of year t
5837 Value Weight Average of BE_FYt-1/ME_June t Calculated for June of t to June of t+1 as:
5838 Sum[ME(Mth) * BE(Fiscal Year t-1) / ME(Jun t)] / Sum[ME(Mth)]
5839 Where Mth is a month from June of t to June of t+1
5840 and BE(Fiscal Year t-1) is adjusted for net stock issuance to Jun t
```

```

6968 For portfolios formed in June of year t
6969 Value Weight Average of OP Calculated as:
6970 Sum[ME(Mth) * OP(fiscal year t-1) / BE(fiscal year t-1)] / Sum[ME(Mth)]
6971 Where Mth is a month from June of t to June of t+1
7655 For portfolios formed in June of year t
7656 Value Weight Average of investment (rate of growth of assets) Calculated as:
7657 Sum[ME(Mth) * Log(ASSET(t-1) / ASSET(t-2) / Sum[ME(Mth)]]
7658 Where Mth is a month from June of t to June of t+1

```

```

In [7]: industry_30 = pd.read_excel(path+"/30_Industry_Portfolios.xlsx")
        for i in range(len(industry_30.iloc[:,0])):
            if not isinstance(industry_30.iloc[i,0],(int,float)):
                print(i,industry_30.iloc[i,0])

        colname = industry_30.iloc[10,:].values
        colname[0] = "Date"
        AVWR_month = industry_30.iloc[11:1135].reset_index().drop("index",axis=1)
        AVWR_month.columns = colname
        AVWR_month["Date"] = pd.to_datetime(AVWR_month["Date"],format = "%Y%m")
        AVWR_month.head()

```

```

0 It contains value- and equal-weighted returns for 30 industry portfolios.
2 The portfolios are constructed at the end of June.
4 The annual returns are from January to December.
6 Missing data are indicated by -99.99 or -999.
9 Average Value Weighted Returns -- Monthly
1137 Average Equal Weighted Returns -- Monthly
2265 Average Value Weighted Returns -- Annual
2362 Average Equal Weighted Returns -- Annual
2459 Number of Firms in Portfolios
3587 Average Firm Size
4715 Sum of BE / Sum of ME
4813 Value-Weighted Average of BE/ME
4910 Copyright 2020 Kenneth R. French

```

```

Out[7]:
      Date Food  Beer  Smoke Games  Books Hshld Clths Hlth  Chems  ...  \
0 1926-07-01  0.56 -5.19  1.29  2.93  10.97 -0.48  8.08  1.77  8.14  ...
1 1926-08-01  2.59 27.03   6.5  0.55  10.01 -3.58 -2.51  4.25   5.5  ...
2 1926-09-01  1.16  4.02  1.26  6.58  -0.99  0.73 -0.51  0.69  5.33  ...
3 1926-10-01 -3.06 -3.31  1.06 -4.76   9.47 -4.68  0.12 -0.57 -4.76  ...
4 1926-11-01  6.35  7.29  4.55  1.66   -5.8 -0.54  1.87  5.42   5.2  ...

      Telcm Servs BusEq Paper Trans  Whlsl Rtail Meals Fin  Other
0  0.83  9.22  2.06   7.7  1.93 -23.79  0.07  1.87  0.37   5.2
1  2.17  2.02  4.39 -2.38  4.88   5.39 -0.75 -0.13  4.46  6.76
2  2.41  2.25  0.19 -5.54  0.05  -7.87  0.25 -0.56 -1.23 -3.86

```

```

3 -0.11    -2 -1.09 -5.08 -2.64 -15.38  -2.2 -4.11 -5.16 -8.49
4  1.63  3.77  3.64  3.84   1.6   4.67  6.52  4.33  2.24   4

```

```
[5 rows x 31 columns]
```

```

In [8]: def get_portfolio_pool(data, J, decile=3):
        res = []
        cumulate = data.rolling(J).sum().dropna()
        slices = [i for i in range(decile)] + [i for i in range(-decile,0)]
        index = cumulate.index
        for i in index:
            sorted_slice = cumulate.sort_values(by = i ,axis = 1, ascending = False)
            res.append(sorted_slice.columns[slices])
        colname = ["long_{}".format(i) for i in range(decile)] + ["short_{}".format(i) for i in range(-decile,0)]
        return pd.DataFrame(res,columns=colname,index=index)

portfolio_pool_6 = get_portfolio_pool(AVWR_month,6,3)
portfolio_pool_9 = get_portfolio_pool(AVWR_month,9,3)
portfolio_pool_6.head()

```

```

Out[8]:  long_0 long_1 long_2 short_3 short_2 short_1
5  Autos  Beer  Chems  Hshld  Paper  Whls1
6  Beer  Books  Txtls  Other  Paper  Whls1
7  Servs  Chems  Txtls  Paper  Other  Whls1
8  Chems  Mines  BusEq  Other  Paper  Whls1
9  Chems  Mines  Autos  Paper  Oil    Whls1

```

```

In [93]: def long_short(month_return, portfolio_pool, K, skip=1):
        index, end = portfolio_pool.index[1+skip:], portfolio_pool.index[-1]
        raw_df = pd.DataFrame(np.zeros((len(index),3)),index=index,columns=["long","short"])
        for i in index:
            hold_index = list(range(i,min(end,i+K)))
            for i in hold_index:
                long = portfolio_pool.loc[i,["long_0","long_1","long_2"]].values
                short = portfolio_pool.loc[i,["short_3","short_2","short_1"]].values
                #print(company_columns)
                raw_df.loc[i,"long"] += month_return.loc[i,long].sum()
                raw_df.loc[i,"short"] += month_return.loc[i,short].sum()
        raw_df["long"] /= 18
        raw_df["short"] /= 18
        raw_df["arbitrage"] = raw_df["long"] - raw_df["short"]
        return raw_df

p66 = long_short(AVWR_month,portfolio_pool_6,6)
p69 = long_short(AVWR_month,portfolio_pool_6,9)
p96 = long_short(AVWR_month,portfolio_pool_9,6)
p99 = long_short(AVWR_month,portfolio_pool_9,9)

```

Because of the t-value is greater than the 95% tscore, all the excess return are significant.

```
In [97]: print(f"df: {p66.shape[0]}")
        print(f"95%t-score: {1.646}")
        print(f't66: {p66["arbitrage"].mean()/p66["arbitrage"].std()*np.sqrt(p66.shape[0])}')
        print(f't69: {p69["arbitrage"].mean()/p69["arbitrage"].std()*np.sqrt(p66.shape[0])}')
        print(f't96: {p96["arbitrage"].mean()/p96["arbitrage"].std()*np.sqrt(p66.shape[0])}')
        print(f't99: {p99["arbitrage"].mean()/p99["arbitrage"].std()*np.sqrt(p66.shape[0])}')
```

```
df: 1117
95%t-score: 1.646
t66: 30.830085692495242
t69: 30.7784947528333
t96: 24.879829686348785
t99: 24.847067914443098
```

```
In [133]: # get rf
        temp_data = pd.read_excel(path+"/F-F_Research_Data_Factors.xlsx")
        rf = temp_data.iloc[3:1127,4].mean()
        Rm = temp_data.iloc[3:1127,2]
        rf *=10
        print(f"rf: {rf}")

        # compute sharpe ratio
        print(f'sharpe ratio 66: {(p66["long"].mean() - rf)/p66["long"].std()}')
        print(f'sharpe ratio 69: {(p69["long"].mean() - rf)/p69["long"].std()}')
        print(f'sharpe ratio 96: {(p96["long"].mean() - rf)/p96["long"].std()}')
        print(f'sharpe ratio 99: {(p99["long"].mean() - rf)/p99["long"].std()}')
        print(f'market portfolio sharpe ratio: {Rm.mean()/Rm.std()}')
        print("All the sharpe ratio of long portfolio are higher than market portfolio")
```

```
rf: 2.7283807829181446
sharpe ratio 66: 0.15099621770830926
sharpe ratio 69: 0.2752308516025211
sharpe ratio 96: 0.0839389006728528
sharpe ratio 99: 0.21009221254283436
market portfolio sharpe ratio: 0.061386904331229016
All the sharpe ratio of long portfolio are higher than market portfolio
```

2 Question 2

```
In [257]: # import model
        from sklearn.linear_model import LinearRegression
        import statsmodels.api as sm
        from scipy import stats

        # load data
```

```

factor_3 = pd.read_excel(path+"/F-F_Research_Data_Factors.xlsx")
name = [factor_3.iloc[2,1]]
CAPM = pd.DataFrame(factor_3.iloc[3:1127,1].values,columns=name)

name = factor_3.iloc[2,:].to_list()
F3 = pd.DataFrame(factor_3.iloc[3:1127,:].values,columns=name)
factor_3.columns = name

factor_5 = pd.read_excel(path+"/F-F_Research_Data_5_Factors_2x3.xlsx")
name = factor_5.iloc[2,:].to_list()
F5 = pd.DataFrame(factor_5.iloc[3:683,:].values,columns=name)

Q = pd.read_excel(path+"/Data_q_factors.xlsx")
Q["Rm-Rf"] = Q["R_MKT"]-Q["R_F"]
name = ["Rm-Rf", "R_ME", "R_IA", "R_ROE",]
Q = pd.DataFrame(Q.loc[2:635,name].values,columns=name)
Q

```

```

Out [257]:
      Rm-Rf    R_ME    R_IA    R_ROE
0    3.5998    1.9517   -1.6933    1.8876
1    3.4921   -0.7446   -2.9519    1.0983
2   -4.5545    2.9132    2.4686    0.5234
3    2.1555    6.2350   -2.1700    0.2945
4    4.2883    3.0119    2.3713   -0.7125
..      ...      ...      ...      ...
629  -2.4087   -4.2469   -0.9351    1.7673
630    1.2450    1.3935    3.0078    1.6828
631    1.6203    0.8401   -0.5515    0.6286
632    3.2577   -0.0261   -1.0127   -1.1667
633    2.5586    1.2822    1.8360   -1.3200

```

```
[634 rows x 4 columns]
```

2.1 66

Almost all the excess return are significant according to the p-value

```

In [328]: # imports
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from scipy import stats

# 66 CAPM
length = np.min([p66.shape[0],CAPM.shape[0]])
y = p66["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = CAPM.iloc[-length:,:].reset_index().drop("index",axis=1)

```

```

lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 CAPM")
print(lm1.summary())

# 66 F3
length = np.min([p66.shape[0],F3.shape[0]])
y = p66["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F3.iloc[-length:,1:4].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 F3")
print(lm1.summary())

# 66 F5
length = np.min([p66.shape[0],F5.shape[0]])
y = p66["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 F5")
print(lm1.summary())

# 66 Q
length = np.min([p66.shape[0],Q.shape[0]])
y = p66["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 Q")
print(lm1.summary())

```

66 CAPM

OLS Regression Results

```

=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.018
Model:                  OLS          Adj. R-squared (uncentered):          0.017
Method:                 Least Squares    F-statistic:                  19.90
Date:                  Tue, 12 May 2020    Prob (F-statistic):          9.00e-06
Time:                  22:32:28          Log-Likelihood:              -3925.6
No. Observations:      1117            AIC:                        7853.
Df Residuals:          1116            BIC:                        7858.
Df Model:               1
Covariance Type:       nonrobust
=====

```

coef	std err	t	P> t	[0.025	0.975]
------	---------	---	------	--------	--------

```

-----
Mkt-RF          0.2019      0.045      4.461      0.000      0.113      0.291
=====
Omnibus:                495.243      Durbin-Watson:                1.060
Prob(Omnibus):          0.000      Jarque-Bera (JB):            5396.868
Skew:                   1.745      Prob(JB):                    0.00
Kurtosis:              13.187      Cond. No.                    1.00
=====

```

Warnings:

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

66 F3

OLS Regression Results

```

=====
Dep. Variable:          arbitrage      R-squared (uncentered):          0.061
Model:                  OLS            Adj. R-squared (uncentered):      0.058
Method:                 Least Squares   F-statistic:                     24.02
Date:                  Tue, 12 May 2020 Prob (F-statistic):              4.58e-15
Time:                  22:32:28         Log-Likelihood:                  -3900.4
No. Observations:      1117           AIC:                             7807.
Df Residuals:          1114           BIC:                             7822.
Df Model:               3
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Mkt-RF          0.0830      0.048      1.730      0.084      -0.011      0.177
SMB              0.2553      0.079      3.232      0.001       0.100      0.410
HML              0.4352      0.070      6.197      0.000       0.297      0.573
=====
Omnibus:                297.371      Durbin-Watson:                1.080
Prob(Omnibus):          0.000      Jarque-Bera (JB):            1344.735
Skew:                   1.176      Prob(JB):                    9.87e-293
Kurtosis:              7.834      Cond. No.                    1.91
=====

```

Warnings:

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

66 F5

OLS Regression Results

```

=====
Dep. Variable:          arbitrage      R-squared (uncentered):          0.069
Model:                  OLS            Adj. R-squared (uncentered):      0.062
Method:                 Least Squares   F-statistic:                     9.966
Date:                  Tue, 12 May 2020 Prob (F-statistic):              3.26e-09
Time:                  22:32:28         Log-Likelihood:                  -2327.6

```

No. Observations: 680 AIC: 4665.
Df Residuals: 675 BIC: 4688.
Df Model: 5
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1803	0.073	2.479	0.013	0.038	0.323
SMB	0.2067	0.103	1.998	0.046	0.004	0.410
HML	-0.3838	0.143	-2.686	0.007	-0.664	-0.103
RMW	0.6056	0.143	4.237	0.000	0.325	0.886
CMA	1.2341	0.211	5.858	0.000	0.820	1.648
Omnibus:	41.356		Durbin-Watson:		1.181	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		63.700	
Skew:	0.468		Prob(JB):		1.47e-14	
Kurtosis:	4.172		Cond. No.		4.00	

Warnings:

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

66 Q

OLS Regression Results

Dep. Variable:	arbitrage	R-squared (uncentered):	0.073			
Model:	OLS	Adj. R-squared (uncentered):	0.066			
Method:	Least Squares	F-statistic:	9.902			
Date:	Tue, 12 May 2020	Prob (F-statistic):	3.95e-09			
Time:	22:32:28	Log-Likelihood:	-2177.5			
No. Observations:	634	AIC:	4365.			
Df Residuals:	629	BIC:	4387.			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Mkt-RF	0.1691	0.075	2.262	0.024	0.022	0.316
SMB	0.1885	0.108	1.740	0.082	-0.024	0.401
HML	-0.4425	0.148	-2.996	0.003	-0.733	-0.152
RMW	0.6266	0.147	4.250	0.000	0.337	0.916
CMA	1.2905	0.220	5.861	0.000	0.858	1.723
=====						
Omnibus:	37.356	Durbin-Watson:	1.197			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	56.116			
Skew:	0.461	Prob(JB):	6.52e-13			
Kurtosis:	4.128	Cond. No.	4.06			

Warnings:

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

2.2 69

Almost all the excess return are significant according to the p-value

```
In [330]: # imports
          from sklearn.linear_model import LinearRegression
          import statsmodels.api as sm
          from scipy import stats

          # 69 CAPM
          length = np.min([p96.shape[0],CAPM.shape[0]])
          y = p69["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = CAPM.iloc[-length:,:].reset_index().drop("index",axis=1)
          lm1 = sm.OLS(y,x.astype(float)).fit()
          print("\n# 66 CAPM")
          print(lm1.summary())

          # 69 F3
          length = np.min([p96.shape[0],F3.shape[0]])
          y = p69["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = F3.iloc[-length:,1:4].reset_index().drop("index",axis=1)
          #print(x)
          lm1 = sm.OLS(y,x.astype(float)).fit()
          print("\n# 66 F3")
          print(lm1.summary())

          # 69 F5
          length = np.min([p96.shape[0],F5.shape[0]])
          y = p69["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
          #print(x)
          lm1 = sm.OLS(y,x.astype(float)).fit()
          print("\n# 66 F5")
          print(lm1.summary())

          # 69 Q
          length = np.min([p96.shape[0],Q.shape[0]])
          y = p69["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
          #print(x)
```

```
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 Q")
print(lm1.summary())
```

66 CAPM

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.017
Model:                  OLS          Adj. R-squared (uncentered):        0.017
Method:                 Least Squares  F-statistic:                  19.77
Date:                  Tue, 12 May 2020  Prob (F-statistic):          9.61e-06
Time:                  22:33:47       Log-Likelihood:              -4377.2
No. Observations:      1117          AIC:                          8756.
Df Residuals:          1116          BIC:                          8762.
Df Model:               1
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.3016	0.068	4.446	0.000	0.168	0.435

```
=====
Omnibus:                497.022    Durbin-Watson:                1.061
Prob(Omnibus):          0.000      Jarque-Bera (JB):              5439.617
Skew:                   1.752      Prob(JB):                      0.00
Kurtosis:               13.228     Cond. No.:                     1.00
=====
```

Warnings:

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

66 F3

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.061
Model:                  OLS          Adj. R-squared (uncentered):        0.058
Method:                 Least Squares  F-statistic:                  24.12
Date:                  Tue, 12 May 2020  Prob (F-statistic):          4.00e-15
Time:                  22:33:47       Log-Likelihood:              -4351.9
No. Observations:      1117          AIC:                          8710.
Df Residuals:          1114          BIC:                          8725.
Df Model:               3
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1225	0.072	1.705	0.088	-0.018	0.264
SMB	0.3851	0.118	3.253	0.001	0.153	0.617

HML	0.6541	0.105	6.218	0.000	0.448	0.861
-----	--------	-------	-------	-------	-------	-------

```
=====
```

Omnibus:	298.515	Durbin-Watson:	1.082
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1354.216
Skew:	1.180	Prob(JB):	8.62e-295
Kurtosis:	7.851	Cond. No.	1.91

```
=====
```

Warnings:

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

66 F5

OLS Regression Results

```
=====
```

Dep. Variable:	arbitrage	R-squared (uncentered):	0.069
Model:	OLS	Adj. R-squared (uncentered):	0.062
Method:	Least Squares	F-statistic:	9.966
Date:	Tue, 12 May 2020	Prob (F-statistic):	3.26e-09
Time:	22:33:47	Log-Likelihood:	-2603.4
No. Observations:	680	AIC:	5217.
Df Residuals:	675	BIC:	5239.
Df Model:	5		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.2705	0.109	2.479	0.013	0.056	0.485
SMB	0.3100	0.155	1.998	0.046	0.005	0.615
HML	-0.5756	0.214	-2.686	0.007	-0.996	-0.155
RMW	0.9084	0.214	4.237	0.000	0.487	1.329
CMA	1.8511	0.316	5.858	0.000	1.231	2.472

```
=====
```

Omnibus:	41.356	Durbin-Watson:	1.181
Prob(Omnibus):	0.000	Jarque-Bera (JB):	63.700
Skew:	0.468	Prob(JB):	1.47e-14
Kurtosis:	4.172	Cond. No.	4.00

```
=====
```

Warnings:

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

66 Q

OLS Regression Results

```
=====
```

Dep. Variable:	arbitrage	R-squared (uncentered):	0.073
Model:	OLS	Adj. R-squared (uncentered):	0.066
Method:	Least Squares	F-statistic:	9.902
Date:	Tue, 12 May 2020	Prob (F-statistic):	3.95e-09

```

Time:                22:33:47    Log-Likelihood:                -2434.6
No. Observations:    634        AIC:                        4879.
Df Residuals:        629        BIC:                        4901.
Df Model:            5
Covariance Type:      nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.2537	0.112	2.262	0.024	0.033	0.474
SMB	0.2828	0.162	1.740	0.082	-0.036	0.602
HML	-0.6638	0.222	-2.996	0.003	-1.099	-0.229
RMW	0.9399	0.221	4.250	0.000	0.506	1.374
CMA	1.9357	0.330	5.861	0.000	1.287	2.584
Omnibus:	37.356		Durbin-Watson:		1.197	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		56.116	
Skew:	0.461		Prob(JB):		6.52e-13	
Kurtosis:	4.128		Cond. No.		4.06	

Warnings:

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

2.3 96

Almost all the excess return are significant according to the p-value. Except Rm-Rf in all the model, and SMB in the last one

```

In [332]: # imports
          from sklearn.linear_model import LinearRegression
          import statsmodels.api as sm
          from scipy import stats

          # 96 CAPM
          length = np.min([p96.shape[0],CAPM.shape[0]])
          y = p96["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = CAPM.iloc[-length:,:].reset_index().drop("index",axis=1)
          lm1 = sm.OLS(y,x.astype(float)).fit()
          print("\n# 66 CAPM")
          print(lm1.summary())

          # 96 F3
          length = np.min([p96.shape[0],F3.shape[0]])
          y = p96["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = F3.iloc[-length:,1:4].reset_index().drop("index",axis=1)

```

```

#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 F3")
print(lm1.summary())

# 69 F5
length = np.min([p96.shape[0],F5.shape[0]])
y = p96["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 F5")
print(lm1.summary())

# 96 Q
length = np.min([p96.shape[0],Q.shape[0]])
y = p96["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 66 Q")
print(lm1.summary())

```

66 CAPM

OLS Regression Results

=====						
Dep. Variable:	arbitrage		R-squared (uncentered):		0.010	
Model:	OLS		Adj. R-squared (uncentered):		0.009	
Method:	Least Squares		F-statistic:		11.13	
Date:	Tue, 12 May 2020		Prob (F-statistic):		0.000878	
Time:	22:34:54		Log-Likelihood:		-3835.7	
No. Observations:	1114		AIC:		7673.	
Df Residuals:	1113		BIC:		7678.	
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Mkt-RF	0.1407	0.042	3.336	0.001	0.058	0.223
=====						
Omnibus:	417.570		Durbin-Watson:		1.286	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		3746.558	
Skew:	1.470		Prob(JB):		0.00	
Kurtosis:	11.489		Cond. No.		1.00	
=====						

Warnings:

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

66 F3

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.039
Model:                  OLS          Adj. R-squared (uncentered):        0.037
Method:                 Least Squares    F-statistic:                  15.07
Date:                  Tue, 12 May 2020    Prob (F-statistic):          1.28e-09
Time:                  22:34:54          Log-Likelihood:              -3819.0
No. Observations:      1114            AIC:                        7644.
Df Residuals:          1111            BIC:                        7659.
Df Model:              3
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.0466	0.045	1.036	0.300	-0.042	0.135
SMB	0.2280	0.074	3.075	0.002	0.083	0.374
HML	0.3131	0.066	4.749	0.000	0.184	0.442

```
=====
Omnibus:                252.413    Durbin-Watson:                1.314
Prob(Omnibus):          0.000    Jarque-Bera (JB):             1128.400
Skew:                   0.992    Prob(JB):                     9.36e-246
Kurtosis:               7.514    Cond. No.:                    1.91
=====
```

Warnings:

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

66 F5

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.061
Model:                  OLS          Adj. R-squared (uncentered):        0.054
Method:                 Least Squares    F-statistic:                  8.731
Date:                  Tue, 12 May 2020    Prob (F-statistic):          4.90e-08
Time:                  22:34:54          Log-Likelihood:              -2287.4
No. Observations:      680            AIC:                        4585.
Df Residuals:          675            BIC:                        4607.
Df Model:              5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1085	0.069	1.583	0.114	-0.026	0.243
SMB	0.1955	0.097	2.005	0.045	0.004	0.387

HML	-0.4186	0.135	-3.109	0.002	-0.683	-0.154
RMW	0.5852	0.135	4.345	0.000	0.321	0.850
CMA	1.0826	0.199	5.453	0.000	0.693	1.472

```
=====
Omnibus:                45.964    Durbin-Watson:                1.370
Prob(Omnibus):           0.000    Jarque-Bera (JB):         88.721
Skew:                    0.435    Prob(JB):                 5.43e-20
Kurtosis:                4.541    Cond. No.                  4.00
=====
```

Warnings:

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

66 Q

OLS Regression Results

```
=====
Dep. Variable:            arbitrage    R-squared (uncentered):        0.067
Model:                    OLS          Adj. R-squared (uncentered):    0.060
Method:                   Least Squares    F-statistic:                  9.066
Date:                     Tue, 12 May 2020    Prob (F-statistic):          2.46e-08
Time:                     22:34:54          Log-Likelihood:               -2140.6
No. Observations:         634              AIC:                         4291.
Df Residuals:              629              BIC:                         4313.
Df Model:                  5
Covariance Type:          nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1051	0.071	1.490	0.137	-0.033	0.244
SMB	0.1582	0.102	1.548	0.122	-0.043	0.359
HML	-0.4845	0.139	-3.478	0.001	-0.758	-0.211
RMW	0.5822	0.139	4.185	0.000	0.309	0.855
CMA	1.1796	0.208	5.679	0.000	0.772	1.588

```
=====
Omnibus:                41.397    Durbin-Watson:                1.396
Prob(Omnibus):           0.000    Jarque-Bera (JB):         77.511
Skew:                    0.427    Prob(JB):                 1.47e-17
Kurtosis:                4.485    Cond. No.                  4.06
=====
```

Warnings:

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

2.4 99

Almost all the excess return are significant according to the p-value. except the Rm-Rf in all the model

```

In [333]: # imports
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from scipy import stats

# 99 CAPM
length = np.min([p99.shape[0],CAPM.shape[0]])
y = p99["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = CAPM.iloc[-length:,:].reset_index().drop("index",axis=1)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 99 CAPM")
print(lm1.summary())

# 99 F3
length = np.min([p99.shape[0],F3.shape[0]])
y = p99["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F3.iloc[-length:,1:4].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 99 F3")
print(lm1.summary())

# 99 F5
length = np.min([p99.shape[0],F5.shape[0]])
y = p99["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 99 F5")
print(lm1.summary())

# 99 Q
length = np.min([p99.shape[0],Q.shape[0]])
y = p99["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# 99 Q")
print(lm1.summary())

```

```
# 99 CAPM
```

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.010
```



```

Model: OLS Adj. R-squared (uncentered): 0.009
Method: Least Squares F-statistic: 10.98
Date: Tue, 12 May 2020 Prob (F-statistic): 0.000952
Time: 22:35:59 Log-Likelihood: -4286.7
No. Observations: 1114 AIC: 8575.
Df Residuals: 1113 BIC: 8580.
Df Model: 1
Covariance Type: nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Mkt-RF      0.2094      0.063      3.313      0.001      0.085      0.333
=====
Omnibus:      418.791      Durbin-Watson:      1.286
Prob(Omnibus):      0.000      Jarque-Bera (JB):      3770.311
Skew:      1.474      Prob(JB):      0.00
Kurtosis:      11.517      Cond. No.      1.00
=====

```

Warnings:

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

99 F3

OLS Regression Results

```

=====
Dep. Variable:      arbitrage      R-squared (uncentered):      0.039
Model: OLS Adj. R-squared (uncentered):      0.037
Method: Least Squares F-statistic:      15.10
Date: Tue, 12 May 2020 Prob (F-statistic):      1.23e-09
Time: 22:35:59 Log-Likelihood:      -4269.9
No. Observations:      1114 AIC:      8546.
Df Residuals:      1111 BIC:      8561.
Df Model:      3
Covariance Type:      nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Mkt-RF      0.0681      0.067      1.008      0.313      -0.064      0.200
SMB      0.3425      0.111      3.081      0.002      0.124      0.561
HML      0.4712      0.099      4.768      0.000      0.277      0.665
=====
Omnibus:      253.194      Durbin-Watson:      1.314
Prob(Omnibus):      0.000      Jarque-Bera (JB):      1133.800
Skew:      0.995      Prob(JB):      6.29e-247
Kurtosis:      7.524      Cond. No.      1.91
=====

```

Warnings:

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

99 F5

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.061
Model:                  OLS          Adj. R-squared (uncentered):        0.054
Method:                 Least Squares  F-statistic:                  8.731
Date:                  Tue, 12 May 2020  Prob (F-statistic):          4.90e-08
Time:                  22:35:59       Log-Likelihood:                -2563.1
No. Observations:      680           AIC:                          5136.
Df Residuals:          675           BIC:                          5159.
Df Model:              5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1628	0.103	1.583	0.114	-0.039	0.365
SMB	0.2933	0.146	2.005	0.045	0.006	0.580
HML	-0.6279	0.202	-3.109	0.002	-1.024	-0.231
RMW	0.8778	0.202	4.345	0.000	0.481	1.275
CMA	1.6240	0.298	5.453	0.000	1.039	2.209

```
=====
Omnibus:                45.964    Durbin-Watson:                1.370
Prob(Omnibus):          0.000    Jarque-Bera (JB):            88.721
Skew:                   0.435    Prob(JB):                    5.43e-20
Kurtosis:               4.541    Cond. No.                     4.00
=====
```

Warnings:

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

99 Q

OLS Regression Results

```
=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.067
Model:                  OLS          Adj. R-squared (uncentered):        0.060
Method:                 Least Squares  F-statistic:                  9.066
Date:                  Tue, 12 May 2020  Prob (F-statistic):          2.46e-08
Time:                  22:35:59       Log-Likelihood:                -2397.6
No. Observations:      634           AIC:                          4805.
Df Residuals:          629           BIC:                          4828.
Df Model:              5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.1576	0.106	1.490	0.137	-0.050	0.365

SMB	0.2372	0.153	1.548	0.122	-0.064	0.538
HML	-0.7268	0.209	-3.478	0.001	-1.137	-0.316
RMW	0.8732	0.209	4.185	0.000	0.464	1.283
CMA	1.7695	0.312	5.679	0.000	1.158	2.381

```
=====
Omnibus:                41.397    Durbin-Watson:                1.396
Prob(Omnibus):          0.000    Jarque-Bera (JB):        77.511
Skew:                   0.427    Prob(JB):                1.47e-17
Kurtosis:               4.485    Cond. No.                4.06
=====
```

Warnings:

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

3 Question 3

In [380]: # load data

```
data = pd.read_excel(path+"/25_Portfolios_5x5.xlsx")
name = data.iloc[14,:].to_list()
new_data = pd.DataFrame(data.iloc[15:1139,:].values,columns=name)
new_data.head()
```

```
Out[380]:      NaN SMALL LoBM ME1 BM2 ME1 BM3 ME1 BM4 SMALL HiBM ME2 BM1 ME2 BM2 \
0  192607      3.7782 -0.4119 -1.9434  0.353      2.0534  2.1904  2.4192
1  192608     -2.2074 -8.7275  2.4404  0.6086      8.3968  2.1709 -1.1849
2  192609     -6.2113 -0.2989 -6.1982 -1.6368      0.8649 -1.855 -1.2618
3  192610     -8.6241 -3.7532 -5.6719  5.717     -2.5476 -1.7995 -3.2663
4  192611      3.4744  6.6476  2.2634 -4.702      0.5362  2.9051 -2.369

      ME2 BM3 ME2 BM4  ... ME4 BM1 ME4 BM2 ME4 BM3 ME4 BM4 ME4 BM5 BIG LoBM \
0  0.4926 -1.577  ...  1.5893  1.5278  1.1869  0.2727  2.4678  3.4539
1  4.0084  0.4643  ...  1.3336  3.873  2.0059  2.1706  5.3422  1.0124
2  1.0829 -3.0405  ...  1.0923 -0.525 -1.7314  1.4646  0.873 -1.2906
3 -5.0745 -8.045  ... -3.3361 -2.6559 -2.0316 -3.1051 -5.3525 -2.7413
4  3.0078  4.6649  ...  3.4448  2.3887  3.7403  4.932  1.8213  4.2946

      ME5 BM2 ME5 BM3 ME5 BM4 BIG HiBM
0  6.0902  2.0266  3.1111  0.5623
1  4.1903  2.0131  5.4849  7.7576
2  3.6538  0.095 -0.7487 -2.4284
3 -3.0071 -2.2437 -4.6719 -5.8129
4  2.5326  1.5204  3.6619  2.5636

[5 rows x 26 columns]
```

In [396]: # use the function from question 1

```
portfolio_pool_5 = get_portfolio_pool(new_data.iloc[:,1:],5,3)
```

```
portfolio_pool_5
```

```
def short_long(month_return, portfolio_pool, K, skip=1):
    index, end = portfolio_pool.index[1+skip:], portfolio_pool.index[-1]
    raw_df = pd.DataFrame(np.zeros((len(index),3)),index=index,columns=["long","short"])
    for i in index:
        hold_index = list(range(i,min(end,i+K)))
        for i in hold_index:
            long = portfolio_pool.loc[i,["long_0","long_1","long_2"]].values
            short = portfolio_pool.loc[i,["short_3","short_2","short_1"]].values
            #print(company_columns)
            raw_df.loc[i,"long"] += month_return.loc[i,long].sum()
            raw_df.loc[i,"short"] += month_return.loc[i,short].sum()
    raw_df["long"] /= 60
    raw_df["short"] /= 60
    raw_df["arbitrage"] = raw_df["short"] - raw_df["long"]
    return raw_df
```

```
q3 = long_short(new_data,portfolio_pool_5,5)
```

It is significant greater than zero

```
In [398]: print(f"df: {q3.shape[0]}")
          print(f"95%t-score: {1.646}")
          print(f't66: {q3["arbitrage"].mean()/q3["arbitrage"].std()*np.sqrt(q3.shape[0])}')
df: 1118
95%t-score: 1.646
t66: 19.81441972208044
```

```
df: 1118
95%t-score: 1.646
t66: 19.81441972208044
```

According to the t-value Except for Rm-Rf, RMW in 5 factor model, and HXZ 1-factor mode are not significant, all other parameters are significant

```
In [399]: # imports
          from sklearn.linear_model import LinearRegression
          import statsmodels.api as sm
          from scipy import stats

          # q3 CAPM
          length = np.min([q3.shape[0],CAPM.shape[0]])
          y = q3["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
          x = CAPM.iloc[-length:,:].reset_index().drop("index",axis=1)
          lm1 = sm.OLS(y,x.astype(float)).fit()
          print("\n# q3 CAPM")
          print(lm1.summary())
```

```

# q3 F3
length = np.min([q3.shape[0],F3.shape[0]])
y = q3["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F3.iloc[-length:,1:4].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# q3 F3")
print(lm1.summary())

# q3 F5
length = np.min([q3.shape[0],F5.shape[0]])
y = q3["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# q3 F5")
print(lm1.summary())

# q3 Q
length = np.min([q3.shape[0],Q.shape[0]])
y = q3["arbitrage"].iloc[-length:].reset_index().drop("index",axis=1)
x = F5.iloc[-length:,1:6].reset_index().drop("index",axis=1)
#print(x)
lm1 = sm.OLS(y,x.astype(float)).fit()
print("\n# q3 Q")
print(lm1.summary())

```

q3 CAPM

OLS Regression Results

```

=====
Dep. Variable:          arbitrage    R-squared (uncentered):          0.049
Model:                  OLS          Adj. R-squared (uncentered):          0.048
Method:                 Least Squares    F-statistic:                  57.63
Date:                  Tue, 12 May 2020    Prob (F-statistic):          6.65e-14
Time:                  23:20:30          Log-Likelihood:              -3613.1
No. Observations:      1118             AIC:                        7228.
Df Residuals:          1117             BIC:                        7233.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.2590	0.034	7.592	0.000	0.192	0.326

```

=====
Omnibus:                1083.196    Durbin-Watson:                1.261
Prob(Omnibus):           0.000      Jarque-Bera (JB):             87348.981

```

```

Skew:                4.265    Prob(JB):                0.00
Kurtosis:            45.454    Cond. No.                1.00
=====

```

Warnings:

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

q3 F3

OLS Regression Results

```

=====
Dep. Variable:        arbitrage    R-squared (uncentered):        0.246
Model:                OLS          Adj. R-squared (uncentered):    0.244
Method:               Least Squares    F-statistic:                121.1
Date:                 Tue, 12 May 2020    Prob (F-statistic):        7.02e-68
Time:                 23:20:30          Log-Likelihood:             -3483.6
No. Observations:     1118            AIC:                        6973.
Df Residuals:         1115            BIC:                        6988.
Df Model:              3
Covariance Type:      nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.0532	0.033	1.615	0.107	-0.011	0.118
SMB	0.5335	0.054	9.833	0.000	0.427	0.640
HML	0.6432	0.048	13.352	0.000	0.549	0.738

```

=====
Omnibus:              656.093    Durbin-Watson:              1.336
Prob(Omnibus):        0.000     Jarque-Bera (JB):           12990.092
Skew:                 2.300     Prob(JB):                   0.00
Kurtosis:             19.053    Cond. No.:                  1.91
=====

```

Warnings:

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

q3 F5

OLS Regression Results

```

=====
Dep. Variable:        arbitrage    R-squared (uncentered):        0.117
Model:                OLS          Adj. R-squared (uncentered):    0.110
Method:               Least Squares    F-statistic:                17.86
Date:                 Tue, 12 May 2020    Prob (F-statistic):        1.18e-16
Time:                 23:20:30          Log-Likelihood:             -1933.1
No. Observations:     680            AIC:                        3876.
Df Residuals:         675            BIC:                        3899.
Df Model:              5
Covariance Type:      nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	0.0117	0.041	0.286	0.775	-0.068	0.092
SMB	0.3544	0.058	6.120	0.000	0.241	0.468
HML	-0.1734	0.080	-2.168	0.030	-0.330	-0.016
RMW	0.0593	0.080	0.741	0.459	-0.098	0.216
CMA	0.7507	0.118	6.366	0.000	0.519	0.982

Omnibus:	180.779	Durbin-Watson:	1.306
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2628.857
Skew:	0.760	Prob(JB):	0.00
Kurtosis:	12.512	Cond. No.	4.00

Warnings:

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

q3 Q

OLS Regression Results

Dep. Variable:	arbitrage	R-squared (uncentered):	0.117
Model:	OLS	Adj. R-squared (uncentered):	0.110
Method:	Least Squares	F-statistic:	16.71
Date:	Tue, 12 May 2020	Prob (F-statistic):	1.63e-15
Time:	23:20:30	Log-Likelihood:	-1809.7
No. Observations:	634	AIC:	3629.
Df Residuals:	629	BIC:	3652.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Mkt-RF	-0.0008	0.042	-0.020	0.984	-0.083	0.081
SMB	0.3389	0.061	5.589	0.000	0.220	0.458
HML	-0.2212	0.083	-2.675	0.008	-0.384	-0.059
RMW	0.0622	0.083	0.754	0.451	-0.100	0.224
CMA	0.7938	0.123	6.441	0.000	0.552	1.036

Omnibus:	166.971	Durbin-Watson:	1.312
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2346.004
Skew:	0.751	Prob(JB):	0.00
Kurtosis:	12.303	Cond. No.	4.06

Warnings:

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

4 Question 4

In [435]: # load data

```
Q4_data = pd.read_excel(path+"/book_market.xlsx",header =None)
mkt_val = pd.read_csv(path+"/ME.csv")
mkt_val.set_index("Date",inplace=True)
book_val = pd.read_csv(path+"/Book_value.csv")
book_val.set_index("Date",inplace=True)
risk_free_returns = pd.read_csv(path+"/t_bill_returns.csv")
risk_free_returns.set_index("date",inplace=True)
stock_ret = pd.read_csv(path+"/HPR_data.csv")
stock_ret.set_index("date",inplace=True)
mrkt_ret = pd.read_csv(path+"/mrkt_returns.csv")
mrkt_ret.set_index("date",inplace=True)
```

In [436]: import numpy as np

```
stock_ret = stock_ret.apply(lambda x: np.log(x/100 +1)*100, axis=1,result_type='broadcast')
stock_ret = stock_ret.iloc[-179:]
ln_book = book_val.apply(lambda x: np.log(x))
ln_mkt = mkt_val.apply(lambda y: np.log(y))
bk_mkt_ratio = np.subtract(ln_book,ln_mkt)
bk_mkt_ratio.head()
long_ret = []
short_ret = []
arb_ret = []

for i in range(len(stock_ret)):
    if i > 59 and i+1 < len(stock_ret.index):
        expected_returns = {}

        for n in stock_ret.columns:

            BV_MV_lagged = bk_mkt_ratio[n].iloc[0:i].values
            X = np.column_stack((np.repeat(1, len(BV_MV_lagged)),BV_MV_lagged))
            Y = stock_ret[n].iloc[0:i].values

            estimates = np.matmul( np.matmul(np.linalg.inv( np.matmul(np.transpose(X),X)),Y))
            expected_returns[n] = estimates[0] + estimates[1] * bk_mkt_ratio[n].values

sorted_data = sorted(expected_returns.items(),key=lambda x:x[1],reverse=True)
highest = sorted_data[0:3]
lowest = sorted_data[-3:]
unzipped_highest = zip(*highest)
unzipped_lowest = zip(*lowest)
high_three =list(unzipped_highest)[0]
low_three = list(unzipped_lowest)[0]

net_long = 0
```



```

net_short = 0
for j in high_three:
    net_long += stock_ret[j].values[i+1]*(1/3)
for k in low_three:
    net_short += stock_ret[k].values[i+1]*(1/3)

long_ret.append(net_long)
short_ret.append(net_short)
arb_ret.append(net_long - net_short)

```

```

In [430]: # compute t-status
print("arbitrage:")
print(f"return: {np.array(arb_ret).mean()}")
print(f"t-status: {np.array(arb_ret).mean()/np.array(arb_ret).std()}")

print("short:")
print(f"return: {np.array(short_ret).mean()}")
print(f"t-status: {np.array(short_ret).mean()/np.array(long_ret).std()}")

print("long:")
print(f"return: {np.array(long_ret).mean()}")
print(f"t-status: {np.array(long_ret).mean()/np.array(long_ret).std()}")

```

```

arbitrage:
return: 0.0020941903582484445
t-status: 0.04856800066021095
short:
return: 0.01569530610190985
t-status: 0.3494865082381052
long:
return: 0.0177894964601583
t-status: 0.39611772849835214

```

5 question 5

```

In [438]: # load data
stock_ret_no_div = pd.read_csv(path+"/HPR_data_wo_div.csv")
stock_ret_no_div.set_index("date",inplace=True)

log_stock_no_div = stock_ret_no_div.apply(lambda x:np.log(x/100 +1)*100, axis=1,result_name="log")
log_stock_no_div = log_stock_no_div.iloc[-179:]
dp_ratio=np.subtract(stock_ret , log_stock_no_div)

In [439]: long_ret = []
short_ret = []
arb_ret = []

```

```

for i in range(len(stock_ret)):
    if i > 59 and i < len(stock_ret.index)-1:
        expected_returns = {}

        for n in stock_ret.columns:

            DP_ratio = dp_ratio[n].iloc[0:i].values
            X = np.column_stack((np.repeat(1, len(DP_ratio)), DP_ratio))
            Y = stock_ret[n].iloc[0:i].values

            estimates = np.matmul( np.matmul(np.linalg.inv( np.matmul(np.transpose(X), X)), Y))
            expected_returns[n] = estimates[0] + estimates[1] * bk_mkt_ratio[n].values

        sorted_data = sorted(expected_returns.items(), key=lambda x: x[1], reverse=True)
        highest = sorted_data[0:3]
        lowest = sorted_data[-3:]
        unzipped_highest = zip(*highest)
        unzipped_lowest = zip(*lowest)
        high_three = list(unzipped_highest)[0]
        low_three = list(unzipped_lowest)[0]

        net_long = 0
        net_short = 0
        for j in high_three:
            net_long += stock_ret[j].values[i+1]*(1/3)
        for k in low_three:
            net_short += stock_ret[k].values[i+1]*(1/3)

        long_ret.append(net_long)
        short_ret.append(net_short)
        arb_ret.append(net_long - net_short)

```

```

In [440]: # compute t-status
print("arbitrage:")
print(f"return: {np.array(arb_ret).mean()}")
print(f"t-status: {np.array(arb_ret).mean()/np.array(arb_ret).std()}")

print("short:")
print(f"return: {np.array(short_ret).mean()}")
print(f"t-status: {np.array(short_ret).mean()/np.array(long_ret).std()}")

print("long:")
print(f"return: {np.array(long_ret).mean()}")
print(f"t-status: {np.array(long_ret).mean()/np.array(long_ret).std()}")

```

```

arbitrage:
return: 0.0016691245415136299
t-status: 0.03838523936983855

```

```
short:  
return: 0.01635686839374341  
t-status: 0.36376643149168636  
long:  
return: 0.018025992935257036  
t-status: 0.40088670803642246
```