

python_5

February 27, 2024

1 Python Excersie #5: FF 3 Factor Model w/ Factset Data

1.1 Step 1: Load in Facset Data.

```
[ ]: import numpy as np
import pandas as pd
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import seaborn as sns
import requests
import time
import zipfile
import os
```

```
[ ]: data_raw = pd.read_excel('factset_data.xlsx', skiprows=2, index_col=0).iloc[:,
↪-1]
```

Clean up the data on compute log returns.

```
[ ]: data = data_raw.dropna()
data.drop(columns='Composite', inplace=True)
data = data.resample('ME').last().dropna()
securities = ['SP500', 'VFIAX', 'TRBCX', 'CFR']
```

```
[ ]: nav_data = data
nav_data.columns = securities
```

```
[ ]: data.columns = securities

for sec in securities:
    data[f'{sec}_log_return'] = np.log(data[sec] / data[sec].shift(1))
data.dropna(inplace=True)
```

```
[ ]: data.head()
```

```
[ ]:
      SP500   VFIAX  TRBCX   CFR  SP500_log_return  \
Date
2004-03-31  1126.2115  104.01  28.98  42.76         -0.016495
2004-04-30  1107.3048  102.38  28.34  43.30         -0.016930
```

2004-05-31	1120.6831	103.78	28.81	43.82	0.012009
2004-06-30	1140.8356	105.41	29.28	44.75	0.017823
2004-07-31	1101.7195	101.92	27.89	43.02	-0.034889

	VFIAX_log_return	TRBCX_log_return	CFR_log_return
Date			
2004-03-31	-0.018952	-0.009957	0.007983
2004-04-30	-0.015796	-0.022332	0.012550
2004-05-31	0.013582	0.016448	0.011938
2004-06-30	0.015584	0.016182	0.021001
2004-07-31	-0.033669	-0.048636	-0.039426

```
[ ]: data = data.drop(columns=securities).dropna()
```

```
[ ]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 240 entries, 2004-03-31 to 2024-02-29
Freq: ME
Data columns (total 4 columns):
#   Column                Non-Null Count  Dtype
---  -
0   SP500_log_return      240 non-null   float64
1   VFIAX_log_return      240 non-null   float64
2   TRBCX_log_return      240 non-null   float64
3   CFR_log_return        240 non-null   float64
dtypes: float64(4)
memory usage: 9.4 KB
```

```
[ ]: data.head()
```

	SP500_log_return	VFIAX_log_return	TRBCX_log_return	\
Date				
2004-03-31	-0.016495	-0.018952	-0.009957	
2004-04-30	-0.016930	-0.015796	-0.022332	
2004-05-31	0.012009	0.013582	0.016448	
2004-06-30	0.017823	0.015584	0.016182	
2004-07-31	-0.034889	-0.033669	-0.048636	

	CFR_log_return
Date	
2004-03-31	0.007983
2004-04-30	0.012550
2004-05-31	0.011938
2004-06-30	0.021001
2004-07-31	-0.039426

```
[ ]: data.describe()
```

```
[ ]:      SP500_log_return  VFIAX_log_return  TRBCX_log_return  CFR_log_return
count      240.000000      240.000000      240.000000      240.000000
mean         0.006200         0.006193         0.007233         0.003874
std          0.043424         0.043590         0.051237         0.068196
min         -0.185634        -0.183720        -0.207890        -0.340102
25%         -0.017585        -0.018488        -0.015318        -0.034005
50%          0.012115         0.013398         0.013986         0.009644
75%          0.032280         0.032025         0.037897         0.045315
max          0.119421         0.120611         0.139681         0.253125
```

1.2 Step 2: Net Asset Value.

The Net Asset Value (NAV) is calculated differently depending on whether or not the mutual fund is an open or closed end fund. If the fund is open, the NAV is calculated by dividing the total value of the fund by the number of outstanding shares. This is done at the end of the day. The open-end funds issue new shares whenever an investor wants to purchase one, then redeems those shares for cash when the investor wants to sell those shares. This is the most common of the two funds.

The close-end fund behaves more like a traditional stock does. They IPO, and issue an initial amount of shares that are then traded at varying amounts based on a few factors. Because the price of these shares can fluctuate, it is possible to get them at discounts, or have to pay premiums, above the NAV.

```
[ ]: print("First and last 5 NAV data points for T. Rowe Blue Chip Growth Fund")
print(nav_data['TRBCX'].head())
print(nav_data['TRBCX'].tail())
```

First and last 5 NAV data points for T. Rowe Blue Chip Growth Fund

Date

2004-03-31 28.98

2004-04-30 28.34

2004-05-31 28.81

2004-06-30 29.28

2004-07-31 27.89

Freq: ME, Name: TRBCX, dtype: float64

Date

2023-10-31 134.89

2023-11-30 149.54

2023-12-31 149.34

2024-01-31 154.66

2024-02-29 166.08

Freq: ME, Name: TRBCX, dtype: float64

1.3 Step 3: Input FactSet Data into lecture code.

FF dataset download and clean.

```
[ ]: url = 'http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/
      ↪F-F_Research_Data_Factors_CSV.zip'
local_zip_file = 'F-F_Research_Data_Factors_CSV.zip'
```

```
local_path = 'C:/Users/Brady/Dropbox/School Files/FIN 5322 - Investment_↵
↳Analysis/Python 5 - FF 3 Factor Model'
```

```
response = requests.get(url)
with open(local_zip_file, 'wb') as file:
    file.write(response.content)

with zipfile.ZipFile(local_zip_file, 'r') as zip_ref:
    zip_ref.extractall(local_path)

time.sleep(0.5)
os.remove(local_zip_file)
```

```
[ ]: ff_data_raw = pd.read_csv('F-F_Research_Data_Factors.CSV', names=['date', ↵
↳'mkt', 'smb', 'hml', 'rf'], skiprows=4)
ff_data = ff_data_raw.iloc[0:1170, :]
```

```
[ ]: # Clean up the data and convert to log returns.
ff_data.set_index('date', drop=True, inplace=True)
ff_data.index = pd.to_datetime(ff_data.index, format='%Y%m')
ff_data = ff_data.apply(pd.to_numeric, errors='coerce').div(100).map(
    lambda x: np.log(1 + x))
```

```
[ ]: ff_data.tail()
```

```
[ ]:          mkt      smb      hml      rf
date
2023-08-01 -0.024190 -0.032110 -0.010657  0.004490
2023-09-01 -0.053823 -0.025420  0.015086  0.004291
2023-10-01 -0.032420 -0.039469  0.001898  0.004689
2023-11-01  0.084709 -0.000200  0.016267  0.004390
2023-12-01  0.047361  0.061565  0.048219  0.004291
```

```
[ ]: # Merge the two datasets.

# Align date formats.
data.index = data.index.to_period('M').to_timestamp()
ff_data.index = ff_data.index.to_period('M').to_timestamp()
m_data = pd.merge(data, ff_data, how='outer', left_index=True, right_index=True)
m_data.dropna(inplace=True)
m_data = m_data.loc['2004-03-01':'2023-12-01', :]

# Cleaning up some memory.
del data_raw, data, ff_data_raw, ff_data
```

```
[ ]: print(' Merge Data Info '.center(75, '-'))
print(m_data.info())
```

```
print(' Descriptive Stats '.center(75, '-'))
print(m_data.describe())
```

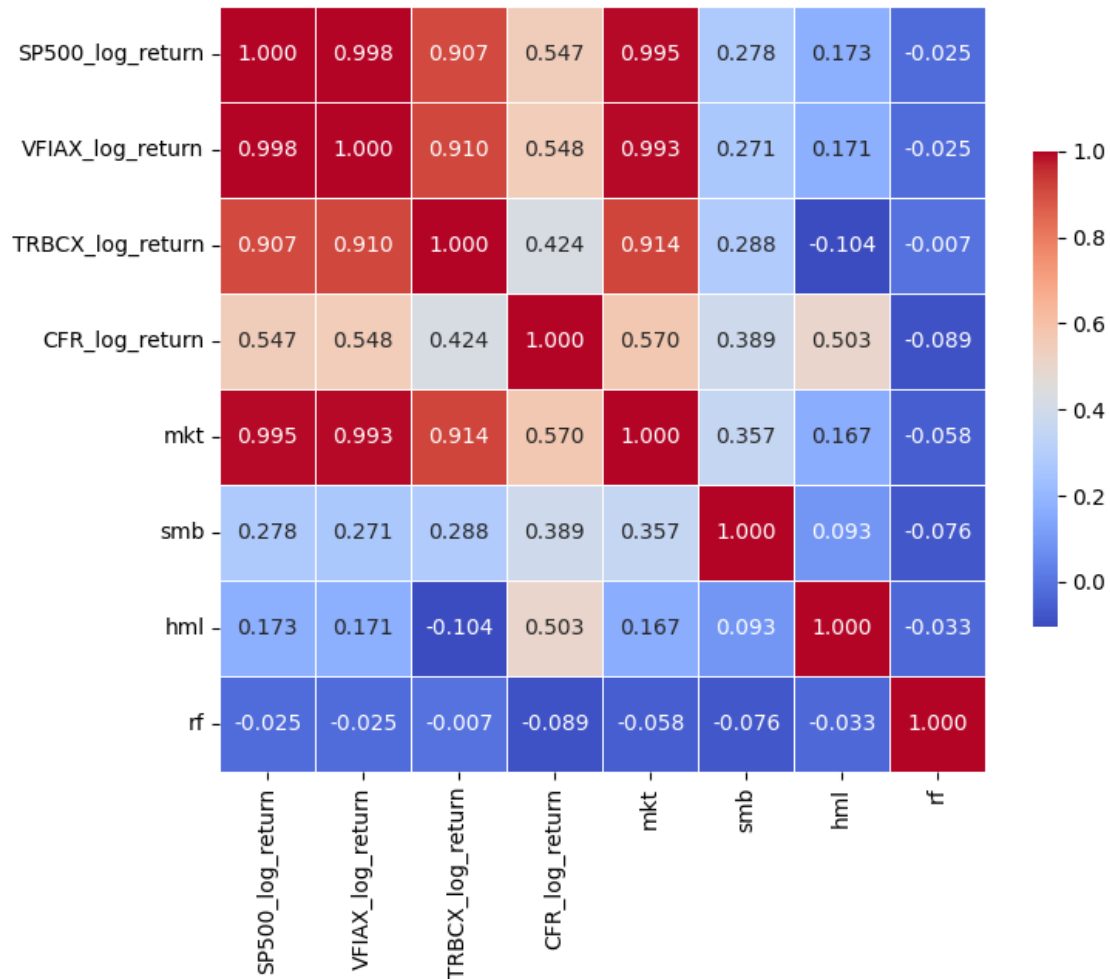
```
----- Merge Data Info -----
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 238 entries, 2004-03-01 to 2023-12-01
Freq: MS
Data columns (total 8 columns):
#   Column                Non-Null Count  Dtype
---  -
0   SP500_log_return      238 non-null   float64
1   VFIAX_log_return      238 non-null   float64
2   TRBCX_log_return      238 non-null   float64
3   CFR_log_return        238 non-null   float64
4   mkt                    238 non-null   float64
5   smb                    238 non-null   float64
6   hml                    238 non-null   float64
7   rf                     238 non-null   float64
dtypes: float64(8)
memory usage: 16.7 KB
None
----- Descriptive Stats -----
      SP500_log_return  VFIAX_log_return  TRBCX_log_return  CFR_log_return  \
count      238.000000      238.000000      238.000000      238.000000
mean         0.005996         0.005980         0.006847         0.003946
std          0.043528         0.043690         0.051251         0.068460
min         -0.185634        -0.183720        -0.207890        -0.340102
25%         -0.017652        -0.018565        -0.015448        -0.034220
50%          0.012062         0.013341         0.013589         0.009644
75%          0.032009         0.032012         0.037848         0.045476
max          0.119421         0.120611         0.139681         0.253125

      mkt          smb          hml          rf
count  238.000000  238.000000  238.000000  238.000000
mean    0.006585    0.000056   -0.001055    0.001125
std     0.044968    0.024632    0.031944    0.001423
min    -0.189105   -0.061237   -0.149312    0.000000
25%    -0.018291   -0.018088   -0.017808    0.000000
50%     0.011780    0.000650   -0.002202    0.000200
75%     0.032540    0.015258    0.013928    0.001798
max     0.127953    0.071017    0.120003    0.004689
```

```
[ ]: corr_matrix = m_data.corr()

plt.figure(figsize=(8,8))
sns.heatmap(corr_matrix, annot=True, fmt=".3f", cmap='coolwarm',
            square=True, linewidths=0.5, cbar_kws={'shrink': 0.5})
```

```
plt.show()
```



Compute betas.

```
[ ]: def y_data(risky_asset, dataframe):
      y = dataframe[risky_asset]
      y.name = f'{risky_asset}'
      return y
```

```
[ ]: m_data.index = m_data.index.strftime('%Y-%m')
```

```
[ ]: risky_assets = ['VFIAX_log_return', 'TRBCX_log_return', 'CFR_log_return']

for risk in risky_assets:
    m_data[f'Ex_{risk}'] = m_data[risk] - m_data['rf']
m_data.columns = m_data.columns.str.replace('_log_return', '_rtn')
m_data.columns = m_data.columns.str.lower()
```

```
[ ]: m_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 238 entries, 2004-03 to 2023-12
Data columns (total 11 columns):
#   Column          Non-Null Count  Dtype
---  -
0   sp500_rtn        238 non-null   float64
1   vfiax_rtn        238 non-null   float64
2   trbcx_rtn        238 non-null   float64
3   cfr_rtn          238 non-null   float64
4   mkt              238 non-null   float64
5   smb              238 non-null   float64
6   hml              238 non-null   float64
7   rf               238 non-null   float64
8   ex_vfiax_rtn     238 non-null   float64
9   ex_trbcx_rtn     238 non-null   float64
10  ex_cfr_rtn       238 non-null   float64
dtypes: float64(11)
memory usage: 22.3+ KB
```

CAPM Model

```
[ ]: # Full regression results.
```

```
asset_analysis = ['ex_cfr_rtn', 'ex_vfiax_rtn', 'ex_trbcx_rtn']

for column in asset_analysis:
    Y = column
    X = 'mkt'
    capm_model = smf.ols(formula=f'{Y} ~ {X}', data=m_data).fit()
    print(f'CAPM Regression Results for {column}'.center(80))
    print(capm_model.summary())

    beta = capm_model.params['mkt']
    r_squared = capm_model.rsquared

    plt.figure(figsize=(6, 4))
    sns.regplot(x='mkt', y=column, data=m_data)
    plt.title(f'CAPM Regression Plot for {column}')
    plt.xlabel('Market Return (mkt)')
    plt.ylabel(f'Excess Return of {column}')
    plt.annotate(f'Beta: {beta:.3f}\nR^2$: {r_squared:.3f}', xy=(0.05,0.85),
                xycoords='axes fraction', fontsize=10)
    plt.show()
```

CAPM Regression Results for ex_cfr_rtn
OLS Regression Results

=====

```

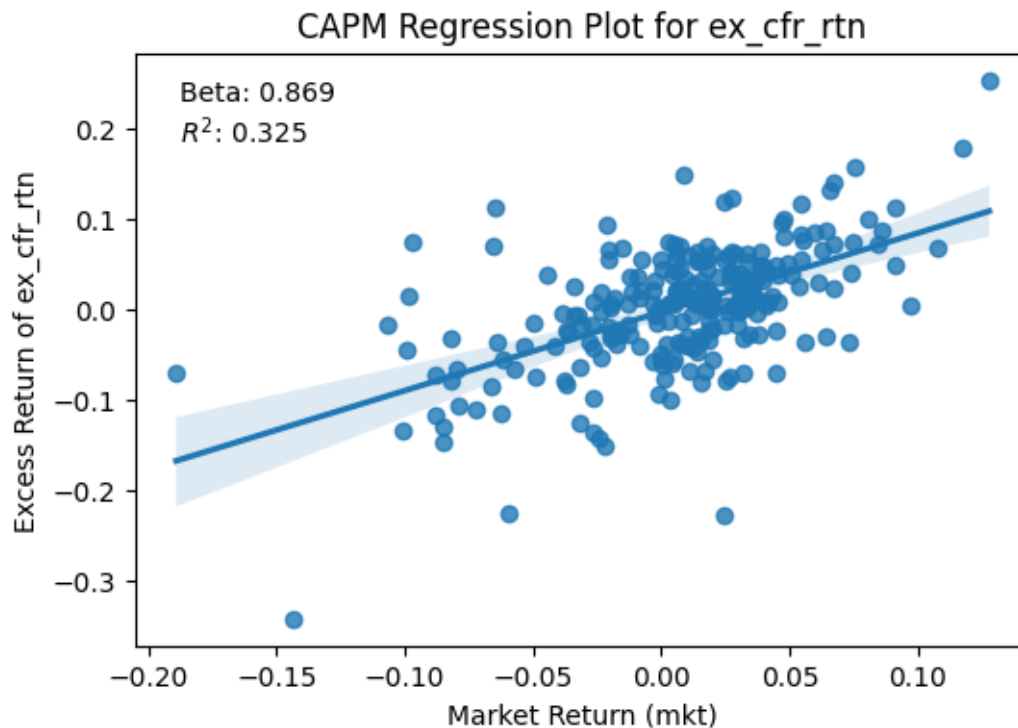
Dep. Variable:          ex_cfr_rtn    R-squared:                0.325
Model:                  OLS           Adj. R-squared:           0.322
Method:                 Least Squares F-statistic:              113.4
Date:                   Tue, 27 Feb 2024 Prob (F-statistic):      7.00e-22
Time:                   10:57:55      Log-Likelihood:          347.20
No. Observations:      238           AIC:                    -690.4
Df Residuals:          236           BIC:                    -683.5
Df Model:               1
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0029	0.004	-0.784	0.434	-0.010	0.004
mkt	0.8691	0.082	10.650	0.000	0.708	1.030
Omnibus:	23.154		Durbin-Watson:	1.887		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	57.445		
Skew:	-0.412		Prob(JB):	3.36e-13		
Kurtosis:	5.262		Cond. No.	22.3		

Notes:

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



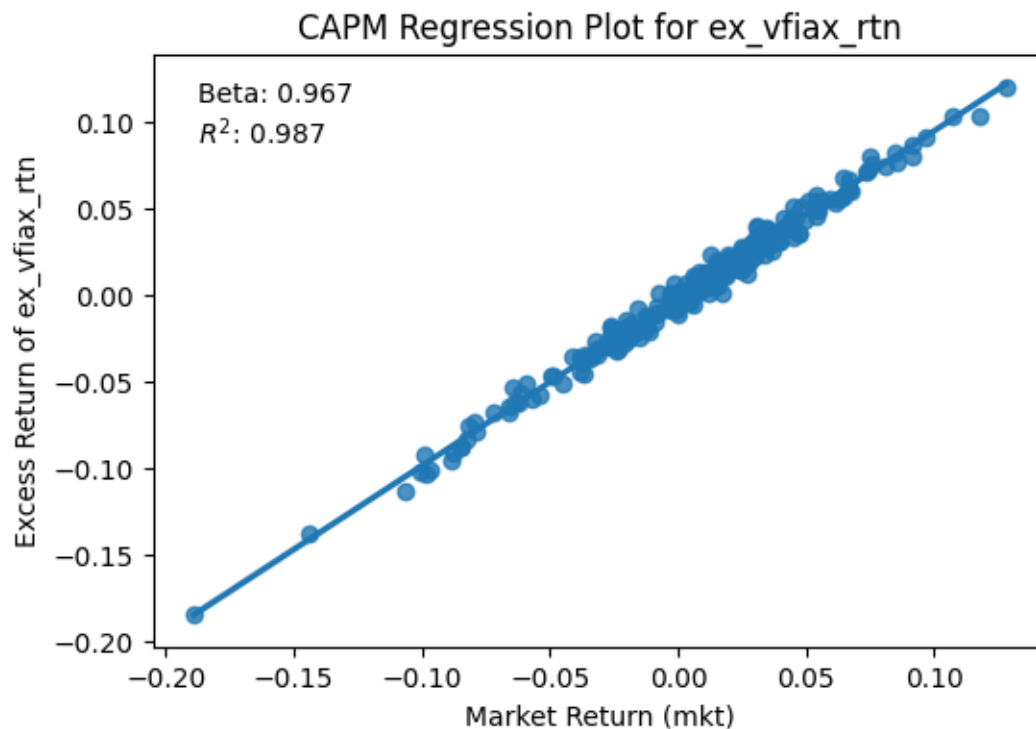
CAPM Regression Results for ex_vfiar_rtn
OLS Regression Results

```
=====
Dep. Variable:          ex_vfiar_rtn    R-squared:                0.987
Model:                  OLS             Adj. R-squared:           0.987
Method:                 Least Squares    F-statistic:             1.854e+04
Date:                   Tue, 27 Feb 2024  Prob (F-statistic):      2.68e-226
Time:                   10:57:55         Log-Likelihood:          928.39
No. Observations:      238              AIC:                     -1853.
Df Residuals:          236              BIC:                     -1846.
Df Model:               1
Covariance Type:       nonrobust
=====
```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -0.0015      0.000     -4.691      0.000     -0.002     -0.001
mkt           0.9668      0.007    136.174      0.000      0.953      0.981
=====
Omnibus:            0.807   Durbin-Watson:           1.992
Prob(Omnibus):      0.668   Jarque-Bera (JB):           0.919
Skew:               0.090   Prob(JB):                 0.632
Kurtosis:           2.754   Cond. No.                  22.3
=====
```

Notes:

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



CAPM Regression Results for ex_trbcx_rtn
OLS Regression Results

```

=====
Dep. Variable:          ex_trbcx_rtn    R-squared:                0.838
Model:                  OLS             Adj. R-squared:           0.837
Method:                 Least Squares   F-statistic:             1222.
Date:                   Tue, 27 Feb 2024 Prob (F-statistic):       2.77e-95
Time:                   10:57:55        Log-Likelihood:          586.43
No. Observations:       238             AIC:                    -1169.
Df Residuals:           236             BIC:                    -1162.
Df Model:                1
Covariance Type:        nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -0.0012      0.001     -0.851      0.396     -0.004      0.002
mkt           1.0440      0.030     34.953      0.000      0.985      1.103
=====

```

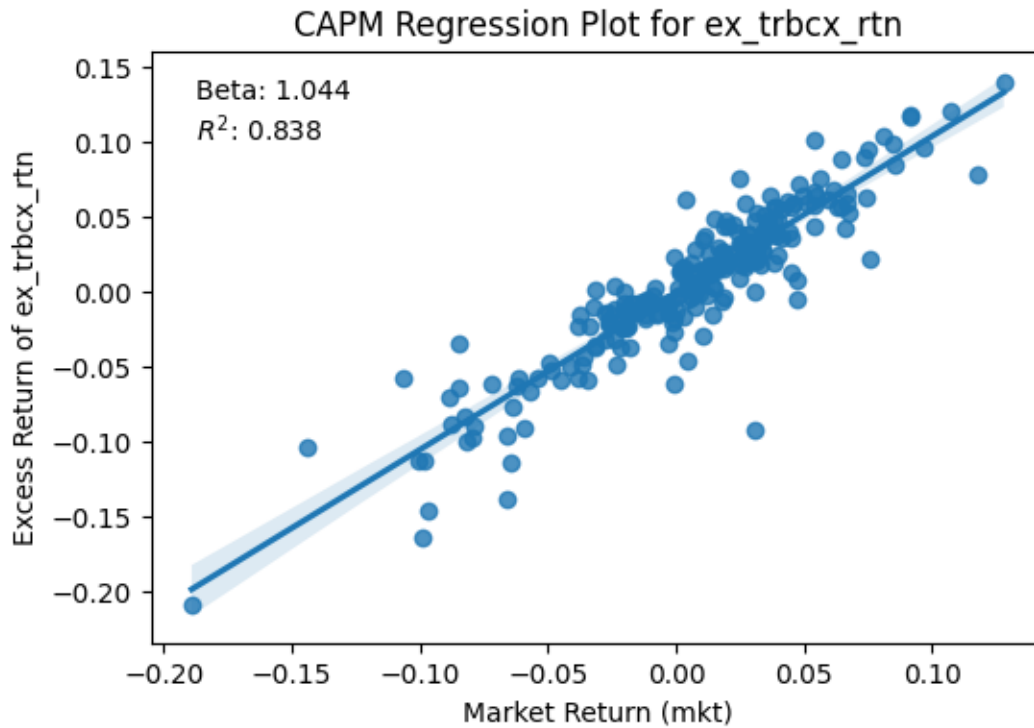
```

=====
Omnibus:            77.364    Durbin-Watson:           1.628
Prob(Omnibus):      0.000    Jarque-Bera (JB):        411.476
Skew:               -1.169    Prob(JB):                4.46e-90
Kurtosis:           9.003    Cond. No.                 22.3
=====

```

Notes:

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



```
[ ]: # Betas from regression.

for column in asset_analysis:
    Y = column
    X = 'mkt'
    capm_model = smf.ols(formula=f'{Y} ~ {X}', data=m_data).fit()
    beta = capm_model.params['mkt']
    r_squared = capm_model.rsquared
    alpha = capm_model.params['Intercept']
    print(f'  FF Beta Stats {column} '.center(40, '=') + '\n')
    print(f'Beta: {beta:.3f}')
    print(f'R-Squared: {r_squared:.3f}')
    print(f'Alpha: {alpha:.3f}\n')
    print(' '.center(40, '=') + '\n')
```

```
=====  FF Beta Stats ex_cfr_rtn  =====
```

Beta: 0.869

R-Squared: 0.325

Alpha: -0.003

=====

===== FF Beta Stats ex_vfiar_rtn =====

Beta: 0.967

R-Squared: 0.987

Alpha: -0.002

=====

===== FF Beta Stats ex_trbcx_rtn =====

Beta: 1.044

R-Squared: 0.838

Alpha: -0.001

=====

Fama and French 3 factor model.

```
[ ]: for column in asset_analysis:
    Y = column
    X = 'mkt + smb + hml'
    ff_model = smf.ols(formula=f'{Y} ~ {X}', data=m_data).fit()
    print(f'3 Factor Model Regression Results for {column}'.center(80))
    print(ff_model.summary())

    beta = ff_model.params['mkt']
    r_squared = ff_model.rsquared

    plt.figure(figsize=(6, 4))
    sns.regplot(x='mkt', y=column, data=m_data)
    plt.title(f'FF Model Regression Plot for {column}')
    plt.xlabel('Market Return (mkt)')
    plt.ylabel(f'Excess Return of {column}')
    plt.annotate(f'Beta: {beta:.3f}\nR^2$: {r_squared:.3f}', xy=(0.05,0.85),
                xycoords='axes fraction', fontsize=10)
    plt.show()
```

3 Factor Model Regression Results for ex_cfr_rtn

OLS Regression Results

```
=====
Dep. Variable:          ex_cfr_rtn    R-squared:                0.530
Model:                  OLS           Adj. R-squared:          0.524
Method:                 Least Squares  F-statistic:             87.82
Date:                   Tue, 27 Feb 2024  Prob (F-statistic):      4.25e-38
```

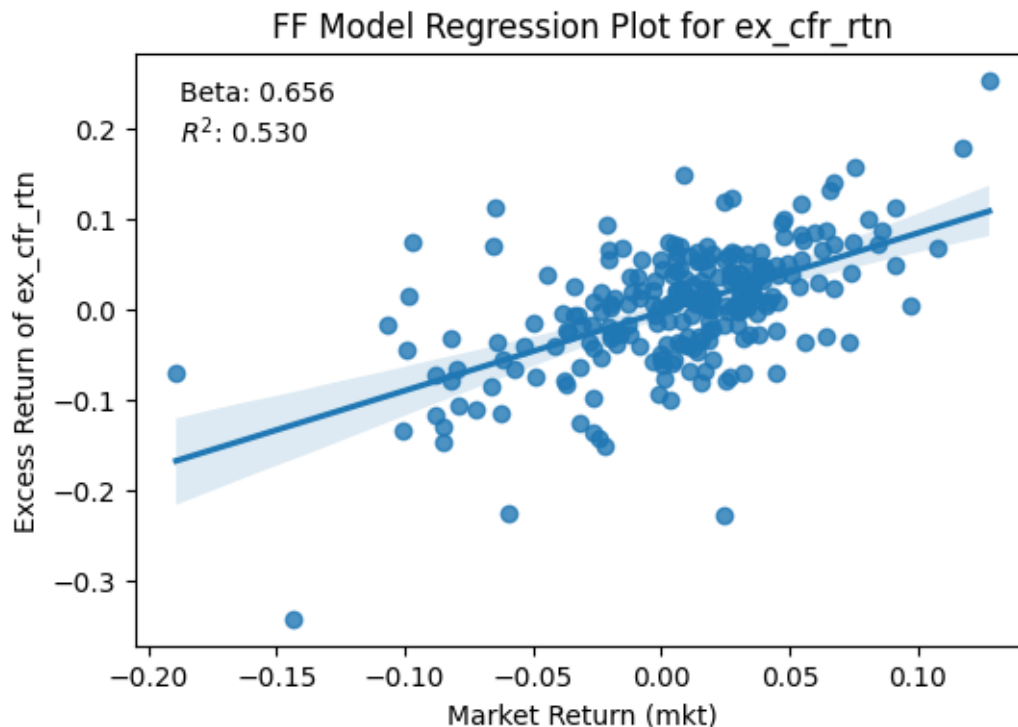
Time: 10:57:55 Log-Likelihood: 390.25
 No. Observations: 238 AIC: -772.5
 Df Residuals: 234 BIC: -758.6
 Df Model: 3
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0006	0.003	-0.192	0.848	-0.007	0.006
mkt	0.6561	0.074	8.867	0.000	0.510	0.802
smb	0.5521	0.134	4.127	0.000	0.289	0.816
hml	0.8856	0.098	9.062	0.000	0.693	1.078

Omnibus: 10.709 Durbin-Watson: 1.897
 Prob(Omnibus): 0.005 Jarque-Bera (JB): 20.312
 Skew: -0.167 Prob(JB): 3.88e-05
 Kurtosis: 4.391 Cond. No. 44.7

Notes:

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



3 Factor Model Regression Results for ex_vfiar_rtn

OLS Regression Results

```

=====
Dep. Variable:          ex_vfiar_rtn      R-squared:                0.995
Model:                  OLS              Adj. R-squared:           0.995
Method:                 Least Squares     F-statistic:             1.609e+04
Date:                  Tue, 27 Feb 2024   Prob (F-statistic):      1.13e-270
Time:                  10:57:55          Log-Likelihood:          1042.3
No. Observations:      238              AIC:                     -2077.
Df Residuals:          234              BIC:                     -2063.
Df Model:               3
Covariance Type:       nonrobust
=====

```

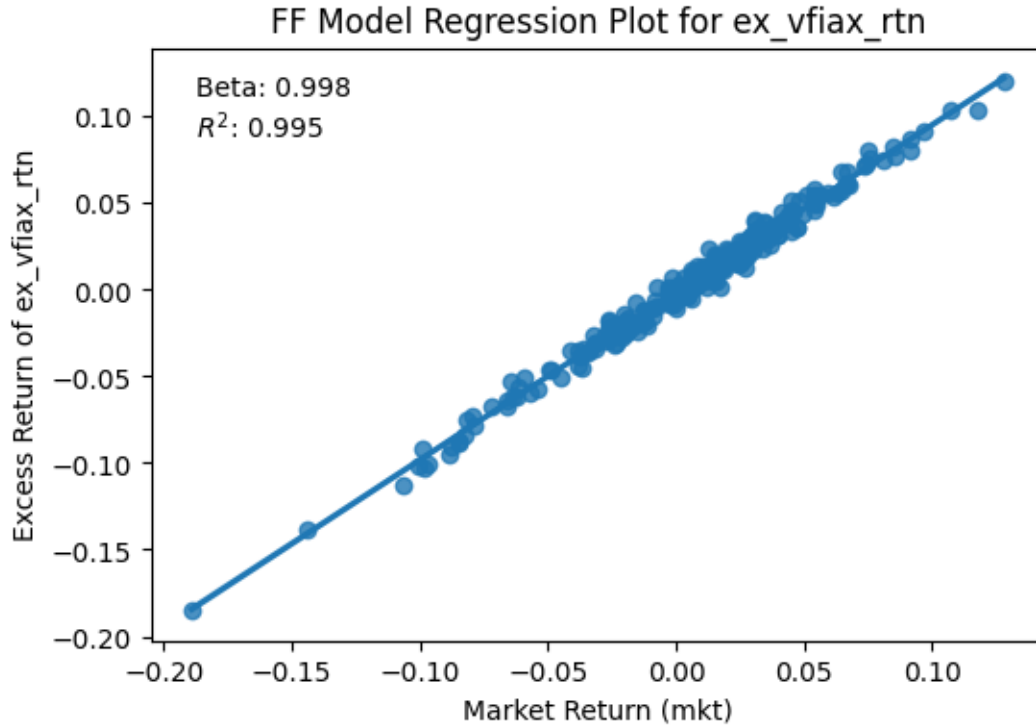
```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    -0.0017      0.000     -8.431      0.000     -0.002     -0.001
mkt           0.9980      0.005    208.827      0.000      0.989      1.007
smb          -0.1671      0.009   -19.340      0.000     -0.184     -0.150
hml           0.0120      0.006      1.905      0.058     -0.000      0.024
=====
Omnibus:                0.024   Durbin-Watson:           2.168
Prob(Omnibus):           0.988   Jarque-Bera (JB):        0.052
Skew:                   -0.023   Prob(JB):                0.974
Kurtosis:                2.945   Cond. No.                 44.7
=====

```

Notes:

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



3 Factor Model Regression Results for ex_trbcx_rtn
OLS Regression Results

```

=====
Dep. Variable:          ex_trbcx_rtn    R-squared:                0.906
Model:                  OLS            Adj. R-squared:          0.905
Method:                 Least Squares   F-statistic:             755.9
Date:                   Tue, 27 Feb 2024 Prob (F-statistic):       4.69e-120
Time:                   10:57:56        Log-Likelihood:          651.72
No. Observations:       238            AIC:                    -1295.
Df Residuals:           234            BIC:                    -1282.
Df Model:                3
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0020	0.001	-1.936	0.054	-0.004	3.52e-05
mkt	1.1070	0.025	44.883	0.000	1.058	1.156
smb	-0.0669	0.045	-1.500	0.135	-0.155	0.021
hml	-0.4211	0.033	-12.928	0.000	-0.485	-0.357

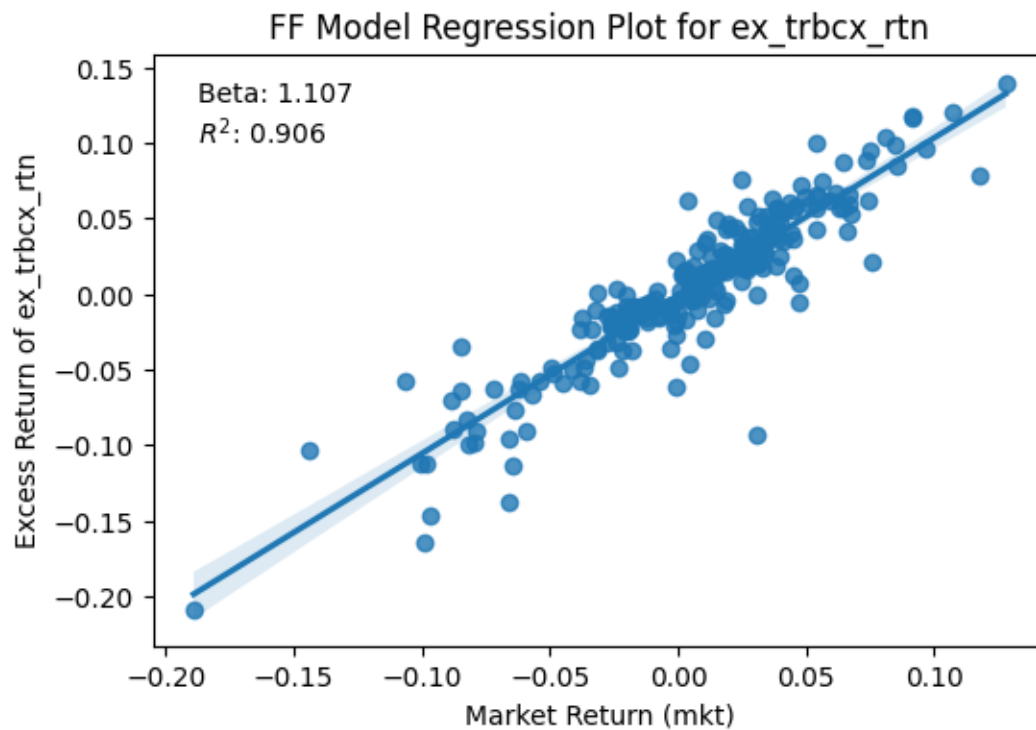
```

=====
Omnibus:                133.229    Durbin-Watson:            1.891
Prob(Omnibus):           0.000    Jarque-Bera (JB):         1313.679
Skew:                    -1.990    Prob(JB):                  5.47e-286
=====

```

Notes:

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



```
[ ]: for column in asset_analysis:
    Y = column
    X = 'mkt + smb + hml'
    ff_model = smf.ols(formula=f'{Y} ~ {X}', data=m_data).fit()
    beta = ff_model.params['mkt']
    r_squared = ff_model.rsquared
    alpha = ff_model.params['Intercept']
    print(f'  FF Beta Stats {column} '.center(40, '=') + '\n')
    print(f'Beta: {beta:.3f}')
    print(f'R-Squared: {r_squared:.3f}')
    print(f'Alpha: {alpha:.3f}\n')
    print(' '.center(40, '=') + '\n')
```

===== FF Beta Stats ex_cfr_rtn =====

Beta: 0.656

R-Squared: 0.530

Alpha: -0.001

=====

===== FF Beta Stats ex_vfiar_rtn =====

Beta: 0.998

R-Squared: 0.995

Alpha: -0.002

=====

===== FF Beta Stats ex_trbcx_rtn =====

Beta: 1.107

R-Squared: 0.906

Alpha: -0.002

=====

Results interpretation. The assets analyzed were Frost banks stock, the Vanguard 500 Index Fund Admiral Shares, and the T. Rowe Price Blue Chip Growth mutual fund.

After running a CAPM regression and a Fama and French 3 factor regression, it is apparent that the index and mutual fund mimick the market relatively close, but all underperformed the market when reviwing their alpha values. I would like to note that the alpha values are in some instances not significant at the 5% level, and should not be considred strong indicators.

Because the index and mutual fund nore closely track the market, their beta's show they are subject to similar sytematic risk of the market. Frost bank on the other hand has a beta less than one, indicating that its vaulation is not tied so closely to the market. This makes sense when considering portfolio construction, especially for the index fund, is trying to mimick the market as best it can.

The R^2 values of each asset are also shown to increase when moving from the CAPM model to the 3 Factor model. This also make sense, as the Fama-French model includes additional parameters, which will boost the R^2 value due to the reduction in unexplained residuals.