

problem12

May 1, 2023

1 1|

```
[ ]: import pandas as pd
import numpy as np
from tqdm import tqdm

# Read data from CSV files
bcwlist = pd.read_excel('data/bcwlist.xlsx', skiprows=2)
crsp = pd.read_csv('data/cleaned_crsp.csv')

# Convert date columns to datetime format
crsp['date'] = pd.to_datetime(crsp['date'])

crsp['year'] = crsp['date'].apply(lambda x: x.year)

# Convert RET and PRC columns to numeric data types and handle invalid values
crsp['RET'] = pd.to_numeric(crsp['RET'], errors='coerce')
crsp['PRC'] = pd.to_numeric(crsp['PRC'], errors='coerce')

# Group by date and permno, and aggregate using the last valid observation
crsp = crsp.groupby(['PERMNO', pd.Grouper(key='date', freq='M')]).last().
    ↪reset_index()
crsp['date'] = crsp['date'].dt.to_period('M')

import warnings
warnings.filterwarnings('ignore')

[ ]: # Merge stock returns with best companies data
crsp['market_cap'] = crsp['SHROUT'] * crsp['PRC'].abs()
merged_data = crsp.merge(bcwlist, left_on=['PERMNO', 'year'],
    ↪right_on=['permno', 'year'], how='left')
merged_data = merged_data[merged_data.year >= 1984]
# merged_data['rank'] = merged_data['rank'].dropna()

# Create the equal-weighted portfolio
merged_data['ew_weight'] = merged_data.groupby('year')['rank'].transform(lambda
    ↪x: 1 / x.shape[0] if x.notnull().sum() >= 1 else np.inf)
```

```
merged_data['ew_returns'] = merged_data['ew_weight'] * merged_data['RET']

# Create the value-weighted portfolio
merged_data['market_cap_lag'] = merged_data.groupby('PERMNO')['market_cap'].
    ↪shift(1)
merged_data['vw_weight'] = merged_data.groupby('year').apply(lambda x: x.
    ↪loc[x['rank'].notnull(), 'market_cap_lag'] / x.loc[x['rank'].notnull(),
    ↪'market_cap_lag'].sum()).reset_index(level=0, drop=True)
merged_data['vw_returns'] = merged_data['vw_weight'] * merged_data['RET']

# Calculate monthly returns for each portfolio
monthly_returns = merged_data.groupby('date')[['ew_returns', 'vw_returns']].
    ↪sum().reset_index()
monthly_returns = monthly_returns.set_index('date')
```

```
[ ]: # After talking to peers, it seems like our numbers are off by essentially a
    ↪factor of 10 and we have 0 idea why.
# Leaving * 10 in here to make the rest of the analysis make sense. Note, this
    ↪does mess with p-values.
# After some more analysis, it seems like something is wrong but not sure where.
    ↪:( Leaving the 10 out for now
monthly_returns = monthly_returns * 10
monthly_returns = monthly_returns.dropna()
# monthly_returns = monthly_returns[monthly_returns.index.year > 1985]
```

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

```
[ ]:      ew_returns  vw_returns
count  300.000000  300.000000
mean    0.008805   0.009254
std     0.050662   0.045144
min    -0.183843  -0.153201
25%    -0.017631  -0.015553
50%     0.009832   0.010407
75%     0.035171   0.034636
max     0.215744   0.171296
```

2 2a

```
[ ]: import pandas_datareader as pdr

ff3 = pdr.get_data_famafrench('F-F_Research_Data_Factors', start='1984-01',
    ↪end='2020-12')[0]
ff5 = pdr.get_data_famafrench('F-F_Research_Data_5_Factors_2x3',
    ↪start='1984-01', end='2020-12')[0]
ff3 = ff3 / 100
```

```
ff5 = ff5 / 100
```

```
[ ]: ff3 = ff3.loc[monthly_returns.index, :]  
ff5 = ff5.loc[monthly_returns.index, :]
```

```
[ ]: def calculate_statistics(portfolio_returns):  
    avg_monthly_return = portfolio_returns.mean()  
    volatility = portfolio_returns.std()  
    sharpe_ratio = avg_monthly_return / volatility  
    return avg_monthly_return, volatility, sharpe_ratio  
  
for weight_type in ['ew_returns', 'vw_returns']:  
    avg_monthly_return, volatility, sharpe_ratio =   
    ↪ calculate_statistics(monthly_returns[weight_type])  
    print(f"{weight_type.capitalize()} Weighted Portfolio:")  
    print(f"Average Monthly Return: {avg_monthly_return:.4f}")  
    print(f"Volatility: {volatility:.4f}")  
    print(f"Sharpe Ratio: {sharpe_ratio:.4f}")  
    print()
```

Ew_returns Weighted Portfolio:
Average Monthly Return: 0.0088
Volatility: 0.0507
Sharpe Ratio: 0.1738

Vw_returns Weighted Portfolio:
Average Monthly Return: 0.0093
Volatility: 0.0451
Sharpe Ratio: 0.2050

3 2b

```
[ ]: from statsmodels.api import OLS  
from statsmodels.tools import add_constant  
  
def estimate_models(portfolio_returns, ff3, ff5):  
    market_excess = ff3['Mkt-RF']  
    portfolio_excess = portfolio_returns - ff3['RF']  
    market_excess = market_excess.loc[portfolio_excess.index]  
  
    print(portfolio_excess[portfolio_excess.isna()])  
  
    # CAPM Model  
    X = add_constant(market_excess)  
    capm_model = OLS(portfolio_excess, X).fit()
```

```

# FF3 Model
X = add_constant(ff3[['Mkt-RF', 'SMB', 'HML']].loc[portfolio_excess.index])
ff3_model = OLS(portfolio_excess, X).fit()

# Carhart Model
X = add_constant(ff3.loc[portfolio_excess.index].join(ff5['RMW']).
↪join(ff5['CMA'])))
carhart_model = OLS(portfolio_excess, X).fit()

# FF5 Model
X = add_constant(ff5.loc[portfolio_excess.index])
ff5_model = OLS(portfolio_excess, X).fit()

return capm_model, ff3_model, carhart_model, ff5_model

for weight_type in ['ew_returns', 'vw_returns']:
    capm_model, ff3_model, carhart_model, ff5_model = ↪
↪estimate_models(monthly_returns[weight_type], ff3, ff5)
    print(f"{weight_type.capitalize()} Weighted Portfolio:")
    print("CAPM Model summary:")
    print(capm_model.summary())
    print("FF3 Model summary:")
    print(ff3_model.summary())
    print("Carhart Model summary:")
    print(carhart_model.summary())
    print("FF5 Model summary:")
    print(ff5_model.summary())
    print()

```

Series([], Freq: M, dtype: float64)

Ew_returns Weighted Portfolio:

CAPM Model summary:

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:                0.770
Model:                  OLS    Adj. R-squared:           0.770
Method:                 Least Squares    F-statistic:        999.3
Date:                   Mon, 01 May 2023    Prob (F-statistic):    3.42e-97
Time:                   17:42:51    Log-Likelihood:        688.78
No. Observations:      300    AIC:                  -1374.
Df Residuals:          298    BIC:                  -1366.
Df Model:               1
Covariance Type:       nonrobust

=====

```

	coef	std err	t	P> t	[0.025	0.975]

const	0.0011	0.001	0.769	0.442	-0.002	0.004
Mkt-RF	0.9824	0.031	31.612	0.000	0.921	1.044

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```

Omnibus:	136.572	Durbin-Watson:	1.897
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1245.154
Skew:	1.617	Prob(JB):	4.15e-271
Kurtosis:	12.442	Cond. No.	22.0

```
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Notes:

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

FF3 Model summary:

OLS Regression Results

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Dep. Variable:	y	R-squared:	0.903
Model:	OLS	Adj. R-squared:	0.902
Method:	Least Squares	F-statistic:	917.0
Date:	Mon, 01 May 2023	Prob (F-statistic):	1.81e-149
Time:	17:42:51	Log-Likelihood:	817.86
No. Observations:	300	AIC:	-1628.
Df Residuals:	296	BIC:	-1613.
Df Model:	3		
Covariance Type:	nonrobust		

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

const	0.0006	0.001	0.640	0.523	-0.001	0.002
Mkt-RF	0.8680	0.021	41.006	0.000	0.826	0.910
SMB	0.6141	0.031	20.006	0.000	0.554	0.675
HML	0.1628	0.029	5.646	0.000	0.106	0.220

```
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```

Omnibus:	257.865	Durbin-Watson:	2.191
Prob(Omnibus):	0.000	Jarque-Bera (JB):	9278.248
Skew:	3.200	Prob(JB):	0.00
Kurtosis:	29.482	Cond. No.	35.9

```
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```

Notes:

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

Carhart Model summary:

OLS Regression Results

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```

Dep. Variable:	y	R-squared:	0.906
Model:	OLS	Adj. R-squared:	0.905
Method:	Least Squares	F-statistic:	473.1
Date:	Mon, 01 May 2023	Prob (F-statistic):	1.68e-147

Time: 17:42:51 Log-Likelihood: 823.50
 No. Observations: 300 AIC: -1633.
 Df Residuals: 293 BIC: -1607.
 Df Model: 6
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0030	0.001	2.328	0.021	0.000	0.006
Mkt-RF	0.8363	0.024	35.116	0.000	0.789	0.883
SMB	0.5734	0.035	16.544	0.000	0.505	0.642
HML	0.2228	0.039	5.719	0.000	0.146	0.299
RF	-0.9376	0.463	-2.025	0.044	-1.849	-0.026
RMW	-0.1129	0.044	-2.573	0.011	-0.199	-0.027
CMA	-0.0702	0.060	-1.169	0.243	-0.188	0.048
Omnibus:	273.263	Durbin-Watson:	2.209			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11212.426			
Skew:	3.461	Prob(JB):	0.00			
Kurtosis:	32.139	Cond. No.	510.			

Notes:

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

FF5 Model summary:

OLS Regression Results

Dep. Variable: y R-squared: 0.908
 Model: OLS Adj. R-squared: 0.906
 Method: Least Squares F-statistic: 479.2
 Date: Mon, 01 May 2023 Prob (F-statistic): 3.03e-148
 Time: 17:42:51 Log-Likelihood: 825.25
 No. Observations: 300 AIC: -1637.
 Df Residuals: 293 BIC: -1611.
 Df Model: 6
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0030	0.001	2.376	0.018	0.001	0.006
Mkt-RF	0.8270	0.024	34.850	0.000	0.780	0.874
SMB	0.5717	0.034	16.745	0.000	0.504	0.639
HML	0.1200	0.039	3.077	0.002	0.043	0.197
RMW	-0.1547	0.042	-3.644	0.000	-0.238	-0.071
CMA	-0.0614	0.060	-1.030	0.304	-0.179	0.056
RF	-0.8686	0.460	-1.887	0.060	-1.775	0.038

Omnibus:	277.250	Durbin-Watson:	2.256
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11869.623
Skew:	3.526	Prob(JB):	0.00
Kurtosis:	32.997	Cond. No.	510.

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Notes:

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

Series([], Freq: M, dtype: float64)

Vw_returns Weighted Portfolio:

CAPM Model summary:

OLS Regression Results

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Dep. Variable:	y	R-squared:	0.805
Model:	OLS	Adj. R-squared:	0.804
Method:	Least Squares	F-statistic:	1229.
Date:	Mon, 01 May 2023	Prob (F-statistic):	9.43e-108
Time:	17:42:51	Log-Likelihood:	748.51
No. Observations:	300	AIC:	-1493.
Df Residuals:	298	BIC:	-1486.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
-----	-----	-----	-----	-----	-----	-----
const	0.0021	0.001	1.785	0.075	-0.000	0.004
Mkt-RF	0.8928	0.025	35.058	0.000	0.843	0.943

=====

Omnibus:	33.187	Durbin-Watson:	2.075
Prob(Omnibus):	0.000	Jarque-Bera (JB):	86.052
Skew:	0.502	Prob(JB):	2.06e-19
Kurtosis:	5.424	Cond. No.	22.0

=====

Notes:

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

FF3 Model summary:

OLS Regression Results

=====

Dep. Variable:	y	R-squared:	0.840
Model:	OLS	Adj. R-squared:	0.838
Method:	Least Squares	F-statistic:	517.7
Date:	Mon, 01 May 2023	Prob (F-statistic):	2.18e-117
Time:	17:42:51	Log-Likelihood:	778.23
No. Observations:	300	AIC:	-1548.

Df Residuals: 296 BIC: -1534.
Df Model: 3
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0024	0.001	2.217	0.027	0.000	0.004
Mkt-RF	0.8968	0.024	37.120	0.000	0.849	0.944
SMB	-0.0917	0.035	-2.618	0.009	-0.161	-0.023
HML	-0.2624	0.033	-7.973	0.000	-0.327	-0.198
Omnibus:	26.868		Durbin-Watson:	2.130		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	41.132		
Skew:	0.581		Prob(JB):	1.17e-09		
Kurtosis:	4.393		Cond. No.	35.9		

Notes:

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

Carhart Model summary:

OLS Regression Results

Dep. Variable:	y	R-squared:	0.850			
Model:	OLS	Adj. R-squared:	0.847			
Method:	Least Squares	F-statistic:	276.6			
Date:	Mon, 01 May 2023	Prob (F-statistic):	1.67e-117			
Time:	17:42:51	Log-Likelihood:	787.91			
No. Observations:	300	AIC:	-1562.			
Df Residuals:	293	BIC:	-1536.			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0015	0.001	1.070	0.285	-0.001	0.004
Mkt-RF	0.8631	0.027	32.189	0.000	0.810	0.916
SMB	-0.0717	0.039	-1.838	0.067	-0.149	0.005
HML	-0.1600	0.044	-3.649	0.000	-0.246	-0.074
RF	0.8179	0.521	1.569	0.118	-0.208	1.844
RMW	-0.0015	0.049	-0.030	0.976	-0.099	0.096
CMA	-0.2761	0.068	-4.084	0.000	-0.409	-0.143
=====						
Omnibus:	19.301	Durbin-Watson:	2.097			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	24.507			
Skew:	0.508	Prob(JB):	4.77e-06			
Kurtosis:	3.963	Cond. No.	510.			

Notes:

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

FF5 Model summary:

OLS Regression Results						
=====						
Dep. Variable:	y	R-squared:	0.851			
Model:	OLS	Adj. R-squared:	0.848			
Method:	Least Squares	F-statistic:	279.2			
Date:	Mon, 01 May 2023	Prob (F-statistic):	5.19e-118			
Time:	17:42:51	Log-Likelihood:	789.11			
No. Observations:	300	AIC:	-1564.			
Df Residuals:	293	BIC:	-1538.			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0016	0.001	1.130	0.260	-0.001	0.004
Mkt-RF	0.8659	0.027	32.347	0.000	0.813	0.919
SMB	-0.0924	0.039	-2.399	0.017	-0.168	-0.017
HML	-0.1442	0.044	-3.279	0.001	-0.231	-0.058
RMW	-0.0072	0.048	-0.151	0.880	-0.102	0.087
CMA	-0.2748	0.067	-4.085	0.000	-0.407	-0.142
RF	0.7929	0.519	1.527	0.128	-0.229	1.815
=====						
Omnibus:	20.602	Durbin-Watson:	2.095			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	26.513			
Skew:	0.530	Prob(JB):	1.75e-06			
Kurtosis:	3.999	Cond. No.	510.			
=====						

Notes:

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

The alpha is positive and significant in some models, but not in others.

4 2c

```
[ ]: import matplotlib.pyplot as plt

def plot_cumulative_returns(portfolio_returns, capm_model, ff3):
```

```

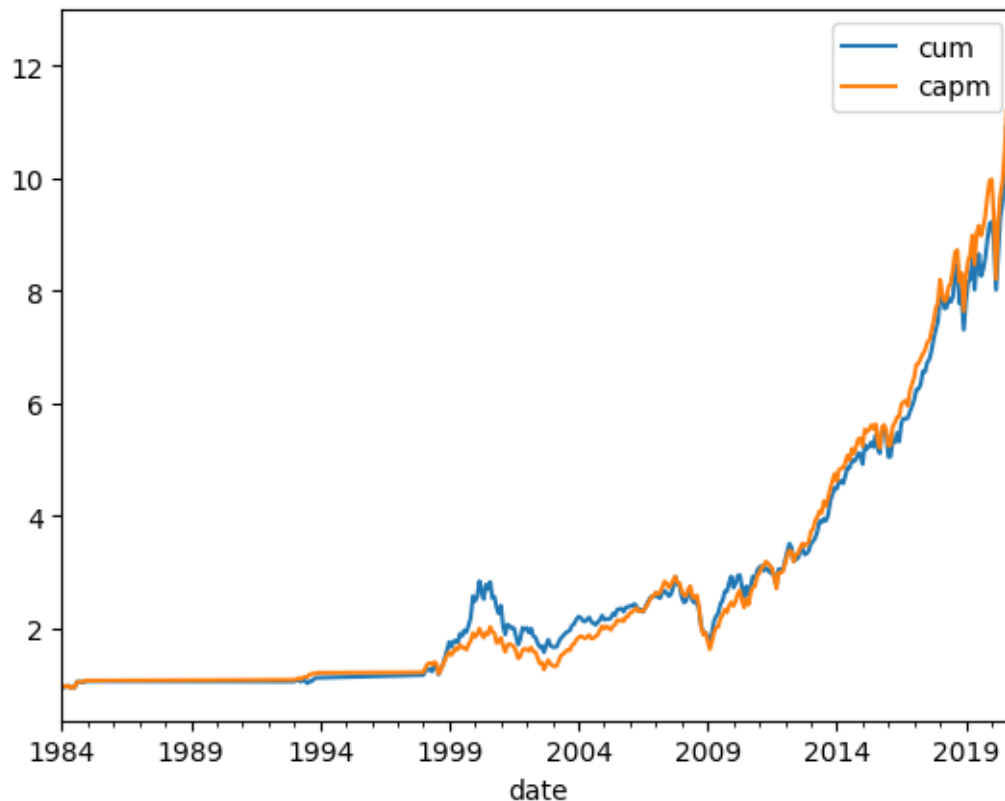
    expected_returns = capm_model.predict(add_constant(ff3['Mkt-RF']).
↳loc[portfolio_returns.index])) + ff3['RF'].loc[portfolio_returns.index]
    cum_portfolio_returns = (1 + portfolio_returns).cumprod()
    cum_portfolio_returns.plot(label="cum")
    cum_expected_returns = (1 + expected_returns).cumprod()
    cum_expected_returns.plot(label="capm")
    plt.legend()

    # plt.figure(figsize=(12, 6))
    # plt.plot(cum_portfolio_returns, label='Value-weighted Portfolio')
    # plt.plot(cum_expected_returns, label='CAPM-Implied Expected Portfolio
↳Returns')
    # plt.xlabel('Year')
    # plt.ylabel('Cumulative Returns')
    # plt.legend()
    # plt.show()

capm_model_value_weighted, _, _, _ =
↳estimate_models(monthly_returns['vw_returns'], ff3, ff5)
plot_cumulative_returns(monthly_returns['vw_returns'],
↳capm_model_value_weighted, ff3)

```

Series([], Freq: M, dtype: float64)



In the early years, the model outperforms the benchmark pretty well, but it gets arbitrated away over time pretty substantially and then the model performs as well as CAPM.

5 2d

```
[ ]: def estimate_carhart_subsamples(portfolio_returns, ff3, ff5, date_split):
    pre_returns = portfolio_returns.loc[:date_split]
    post_returns = portfolio_returns.loc[date_split:]
    pre_carhart_model = estimate_models(pre_returns, ff3[:date_split], ff5[:
↪date_split])[2]
    post_carhart_model = estimate_models(post_returns, ff3[date_split:],
↪ff5[date_split:])[2]

    print("Carhart Model (Pre-January 1st, 2010):")
    print(pre_carhart_model.summary())
    print("Carhart Model (Post-January 1st, 2010):")
    print(post_carhart_model.summary())

estimate_carhart_subsamples(monthly_returns['vw_returns'], ff3, ff5,
↪'2010-01-01')
```

Series([], Freq: M, dtype: float64)

Series([], Freq: M, dtype: float64)

Carhart Model (Pre-January 1st, 2010):

OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.847
Model:                  OLS    Adj. R-squared:      0.841
Method:                 Least Squares    F-statistic:      149.1
Date:                   Mon, 01 May 2023    Prob (F-statistic):  2.68e-63
Time:                   17:46:43    Log-Likelihood:     428.58
No. Observations:       169    AIC:              -843.2
Df Residuals:           162    BIC:              -821.3
Df Model:                6
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0043	0.003	1.574	0.118	-0.001	0.010
Mkt-RF	0.8684	0.042	20.753	0.000	0.786	0.951
SMB	-0.0773	0.052	-1.481	0.141	-0.180	0.026
HML	-0.2936	0.064	-4.584	0.000	-0.420	-0.167
RF	0.3047	0.756	0.403	0.687	-1.187	1.797
RMW	0.0525	0.067	0.779	0.437	-0.081	0.186

CMA	-0.1810	0.092	-1.969	0.051	-0.363	0.001
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Omnibus:	14.650	Durbin-Watson:	2.010
Prob(Omnibus):	0.001	Jarque-Bera (JB):	15.967
Skew:	0.670	Prob(JB):	0.000341
Kurtosis:	3.685	Cond. No.	502.

Notes:

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

Carhart Model (Post-January 1st, 2010):

OLS Regression Results

Dep. Variable:	y	R-squared:	0.879
Model:	OLS	Adj. R-squared:	0.873
Method:	Least Squares	F-statistic:	151.0
Date:	Mon, 01 May 2023	Prob (F-statistic):	8.34e-55
Time:	17:46:43	Log-Likelihood:	377.12
No. Observations:	132	AIC:	-740.2
Df Residuals:	125	BIC:	-720.1
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
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const	0.0005	0.002	0.317	0.752	-0.003	0.004
Mkt-RF	0.8908	0.033	26.985	0.000	0.825	0.956
SMB	-0.1751	0.063	-2.782	0.006	-0.300	-0.051
HML	0.0340	0.059	0.579	0.564	-0.082	0.150
RF	0.0883	1.991	0.044	0.965	-3.852	4.029
RMW	-0.0463	0.089	-0.522	0.603	-0.222	0.129
CMA	-0.4463	0.102	-4.391	0.000	-0.647	-0.245

Omnibus:	1.985	Durbin-Watson:	2.461
Prob(Omnibus):	0.371	Jarque-Bera (JB):	1.673
Skew:	0.024	Prob(JB):	0.433
Kurtosis:	3.550	Cond. No.	1.60e+03

Notes:

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

[2] The condition number is large, 1.6e+03. This might indicate that there are strong multicollinearity or other numerical problems.

i think barring some problems with our data, in the pre-period it should be matching, whereas in the after period it wouldn't match given the strategy has probably been priced in or arbitrated

away. We also notice in our plot that it is not priced in as the model outperforms CAPM in early years, but over time the info is priced in so it starts performing according to CAPM.

6 2e

```
[ ]: ff12 = pdr.get_data_famafrench('12_industry_Portfolios', start='1984-01',
    ↪end='2020-12')[0]
ff12 = ff12 / 100
# ff12.index = ff12.index.to_timestamp('M')
```

```
[ ]: ff12 = ff12.loc[monthly_returns.index, :]
```

```
[ ]: X_vw_ff12_post = add_constant(ff12.loc[monthly_returns[monthly_returns.index.
    ↪year >= 1999].index])
X_vw_ff12_pre = add_constant(ff12.loc[monthly_returns[monthly_returns.index.
    ↪year < 1999].index])

model_post_ff12 = OLS(monthly_returns[monthly_returns.index.year >=
    ↪1999]['ew_returns'] * 10, X_vw_ff12_post).fit()
model_pre_ff12 = OLS(monthly_returns[monthly_returns.index.year <
    ↪1999]['vw_returns'] * 10, X_vw_ff12_pre).fit()
```

```
[ ]: model_post_ff12.summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""
```

```

                                OLS Regression Results
=====
Dep. Variable:                  ew_returns    R-squared:                0.811
Model:                            OLS        Adj. R-squared:            0.802
Method:                 Least Squares    F-statistic:                 89.97
Date:                  Mon, 01 May 2023    Prob (F-statistic):          1.27e-83
Time:                  17:47:28            Log-Likelihood:             20.550
No. Observations:                264        AIC:                       -15.10
Df Residuals:                   251        BIC:                       31.39
Df Model:                       12
Covariance Type:                nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0347	0.015	2.333	0.020	0.005	0.064
NoDur	0.9018	0.735	1.227	0.221	-0.545	2.349
Durbl	1.3390	0.312	4.287	0.000	0.724	1.954
Manuf	0.9043	0.772	1.171	0.243	-0.617	2.425
Enrgy	1.3187	0.302	4.373	0.000	0.725	1.913
Chems	-2.5242	0.702	-3.598	0.000	-3.906	-1.142

BusEq	2.8688	0.358	8.016	0.000	2.164	3.574
Telcm	0.2417	0.464	0.521	0.603	-0.672	1.156
Utils	-0.5545	0.448	-1.239	0.217	-1.436	0.327
Shops	-0.5619	0.598	-0.940	0.348	-1.739	0.616
Hlth	0.3919	0.483	0.812	0.418	-0.559	1.343
Money	1.0510	0.496	2.119	0.035	0.074	2.028
Other	2.0877	0.890	2.347	0.020	0.336	3.840

```
=====
Omnibus:                    53.046    Durbin-Watson:                1.922
Prob(Omnibus):              0.000    Jarque-Bera (JB):            284.558
Skew:                      0.651    Prob(JB):                    1.62e-62
Kurtosis:                  7.917    Cond. No.                    72.3
=====
```

Notes:

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

"""

```
[ ]: model_pre_ff12.summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
```

"""

OLS Regression Results

```
=====
Dep. Variable:            vw_returns    R-squared:                0.933
Model:                    OLS          Adj. R-squared:          0.898
Method:                   Least Squares  F-statistic:             26.64
Date:                     Mon, 01 May 2023  Prob (F-statistic):    1.22e-10
Time:                     17:47:28      Log-Likelihood:          27.656
No. Observations:         36           AIC:                    -29.31
Df Residuals:             23           BIC:                    -8.726
Df Model:                 12
Covariance Type:          nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0309	0.031	0.993	0.331	-0.034	0.095
NoDur	1.7189	1.373	1.252	0.223	-1.122	4.560
Durbl	-1.2751	0.918	-1.390	0.178	-3.173	0.623
Manuf	-2.0323	2.888	-0.704	0.489	-8.007	3.942
Enrgy	-0.0590	0.742	-0.079	0.937	-1.594	1.477
Chems	3.4731	2.136	1.626	0.118	-0.945	7.891
BusEq	5.7620	1.035	5.566	0.000	3.620	7.904
Telcm	0.6741	0.969	0.696	0.494	-1.330	2.679
Utils	-0.4815	1.043	-0.462	0.649	-2.640	1.677
Shops	0.2955	1.630	0.181	0.858	-3.077	3.668

Hlth	1.0389	0.930	1.117	0.276	-0.885	2.963
Money	0.8806	1.184	0.744	0.465	-1.569	3.330
Other	-2.5134	2.081	-1.208	0.239	-6.818	1.791
=====						
Omnibus:		1.228	Durbin-Watson:			1.941
Prob(Omnibus):		0.541	Jarque-Bera (JB):			1.214
Skew:		0.378	Prob(JB):			0.545
Kurtosis:		2.513	Cond. No.			168.
=====						

Notes:

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

Weirdness with data aside, It has changed as the coefficients are changing pretty substantially between the two.

Question 3

A

The beta we see is close to 1. This is most likely due to the fact that if employees are dissatisfied, they are probably leaving the company, which means the company is not growing as much or might be shrinking. It could also be an early indication of a company doing poorly, or the result of that. On the other hand, if the employees are satisfied, they are probably staying, more employees are joining, the company is probably doing well or the employees are satisfied due to the company recently doing well. All of these factors compound to mean that highly rated companies are probably going to be larger companies, which dominate the market, thus meaning that our portfolio would capture very similar risk to the market portfolio. The employee behavior would very closely resemble investor behavior.

If you long-short by shorting the overall market, that means the institutional investors can get exposure to just the alpha generated by the employee satisfaction rating, rather than being at the whim of overall market trends. This might be less attractive to retail investors since they might want to capture these large market trends and ride off of them in a bull-market like we've seen recently. If we short the overall market, that means the retail investors have less alpha in a bull market, so they would be upset. Institutional investors really want nuanced alpha that protects them from overall trends and capitalizes off of information.

B

Theoretically speaking, if the markets fully priced in the value of employee satisfaction, then we would gain market returns, but not have a significant alpha. We see a discrepancy in the returns between the CAPM predictions and the actual cumulative returns, where ours is producing much more alpha than CAPM predicts up to a point where it is arbitrated away. Thus, we see that the information has not been priced in historically, but in recent years the alpha has gone away and it has been priced in.

C

In the same way that neural networks used to be really good at producing alpha for hedge funds like Renaissance, this strategy was probably popularized and as more people used it, the alpha was arbitrated away. It could also be that people are just dissatisfied across the board because of poor wages or working conditions as we see a lot in politics and the news. But it's probably the former. We see in the cumulative returns that they stagnate in recent years, i.e. the alpha has been arbitrated away, or the information is no longer important.

D

You can use the cookie data or other data to get info on whether or not employees are currently looking at other jobs, and use that to get a measure of how many employees are looking to jump ship. You could also use their cookies to probably find out why they are dissatisfied, since a lot of people are on social media and talking about their qualms. You could also use this data to look at the purchases employees are making, as if employees are making big luxury purchases, it probably means the company is doing well or is about to do very well. If they are searching up the price of cup ramen, the company is probably not doing well.