

# BEM114\_HW3\_Andrew\_Daniel\_Kyle

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## 1 BEM114 Homework 3 - Value of Intangibles

**Names:** Andrew Zabelo, Daniel Wen, Kyle McCandless

**Student IDs:** 2176083, 2159859, 2157818

### 1.1 Setup

#### 1.1.1 Imports and Helper Functions

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

from datetime import datetime
from dateutil.relativedelta import relativedelta

import statsmodels.api as sm
import matplotlib.pyplot as plt
```

```
[2]: # Gets the next month from a date string
def get_next_month_str(d1):
    return (datetime.strptime(d1, "%Y-%m") + relativedelta(months=1)).
    ↪strftime("%Y-%m")

def is_next_month(d1, d2):
    return d2 == get_next_month_str(d1)

# Briefly test is_next_month
assert is_next_month('1986-05', '1986-06')
assert is_next_month('2012-12', '2013-01')
assert is_next_month('1999-12', '2000-01')
assert not is_next_month('1986-04', '1986-06')
assert not is_next_month('1998-04', '1999-05')
assert not is_next_month('1984-01', '1986-10')

# Given a group of stocks, calculate equal-weighted and value-weighted weights
def calc_weights(group):
    if group['rebalance'].sum() > 0:
        # Calc equal weights
```

```

        group['weights_eq'] = 1 / float(group['PERMNO'].count())
        assert(group['PERMNO'].count() == group['PERMNO'].nunique())
        # Calc value weights
        group['weights_val'] = group['MV'] / group['MV'].sum()
        return group
    else:
        group['weights_eq'] = np.nan
        group['weights_val'] = np.nan
        return group

# Adds a final month of 0 returns any time a stock becomes de-listed
def add_padding_month(group):
    # Sorted list of dates in this group
    dates_list = sorted([''.join(str_list) for str_list in group['date'].
        ↪agg(list)])

    # Collect de-listing dates
    dates_to_add = [group['date'].max()]
    prev_date = dates_list[0]
    for date in dates_list[1:]:
        if not is_next_month(prev_date, date):
            dates_to_add.append(prev_date)
            prev_date = date

    # Add new padding rows for the month after each de-listing date
    new_rows = []
    for date in dates_to_add:
        new_row = pd.Series({'company': group['company'].iloc[0],
            'PERMNO': group['PERMNO'].iloc[0],
            'date': get_next_month_str(date),
            'RET': 0.0,
            'MV': 1.0})
        new_rows.append(new_row)

    return pd.concat([group, pd.DataFrame(new_rows)], ignore_index=True)

# Calculates returns and prints the returns mean, vol, and Sharpe ratio for a
    ↪strategy
def analyze(returns, strat_name):
    strat_mean = returns.mean()
    strat_vol = returns.std()
    strat_sharpe = strat_mean / strat_vol
    print(f"{strat_name} monthly returns:\nMean = {strat_mean}%\nVolatility =
    ↪{strat_vol}%\nSharpe Ratio = {strat_sharpe}")

# Estimates the CAPM and FF3 models on df_old using the returns found in
    ↪ret_col_name

```

```

def estimate_models(df_old, return_col_name, ff5_mom):
    df = pd.merge(df_old, ff5_mom, how='inner', on=['date'])
    assert(len(df) == len(df_old))

    # Estimate CAPM
    print('CAPM')
    capm_model = sm.OLS(df[return_col_name] - df['RF'], sm.
    ↪add_constant(df[['Mkt-RF']])).fit()
    capm_beta = capm_model.params['Mkt-RF']
    print(capm_model.summary())

    # Estimate FF3
    print('FF3')
    print(sm.OLS(df[return_col_name] - df['RF'], sm.add_constant(df[['Mkt-RF',
    ↪'SMB', 'HML']]))).fit().summary())

    # Estimate Carhart
    print('Carhart')
    print(sm.OLS(df[return_col_name] - df['RF'], sm.add_constant(df[['Mkt-RF',
    ↪'SMB', 'HML', 'MOM']]))).fit().summary())

    # Estimate FF5
    print('FF5')
    print(sm.OLS(df[return_col_name] - df['RF'], sm.add_constant(df[['Mkt-RF',
    ↪'SMB', 'HML', 'RMW', 'CMA']]))).fit().summary())

    return capm_beta

# Plots the cumulative returns for a strategy versus the CAPM-implied returns
def plot_cum_returns(df, return_col_name, capm_beta, title):
    df[return_col_name + '_MIR'] = df['RF'] + capm_beta * df['Mkt-RF']

    dates = df['date'] // 100 + (df['date'] % 100) / 12
    strategy_cumulative = (df[return_col_name] / 100 + 1.0).cumprod()
    mir_cumulative = (df[return_col_name + '_MIR'] / 100 + 1.0).cumprod()
    market_cumulative = ((df['Mkt-RF'] + df['RF']) / 100 + 1.0).cumprod()

    plt.figure()
    plt.plot(dates, strategy_cumulative, label=f'{return_col_name} Portfolio_
    ↪Value')
    plt.plot(dates, mir_cumulative, label=f'CAPM-Implied Portfolio Value')
    plt.plot(dates, market_cumulative, label=f'Market Portfolio Value')

    plt.title(f'{title} Model Performance')
    plt.xlabel('Date')
    plt.ylabel('Cumulative Portfolio Value')

```

```
plt.legend()
plt.show()
```

### 1.1.2 Process Dataframes

```
[3]: '''
Load CRSP data
'''

crsp = pd.read_csv('crsp_1926_2020.zip')

# Convert prices and returns to numeric and drop NaNs
crsp['PRC'] = pd.to_numeric(crsp['PRC'], errors='coerce')
crsp['RET'] = pd.to_numeric(crsp['RET'], errors='coerce')
crsp = crsp.dropna(subset=['PRC', 'RET'])

# Set types for relevant columns
crsp = crsp.astype({'date': 'string', 'SHRCD': 'int', 'EXCHCD': 'int'})

# [From HW2] Filter SHRCD and EXCHCD
crsp = crsp[crsp['SHRCD'].isin([10, 11])]
crsp = crsp[crsp['EXCHCD'].isin([1, 2, 3])]

# Reformat date column and add market value column
crsp['date'] = crsp['date'].str[:3]
crsp['year'] = crsp['date'].str[:3].astype('int')
crsp['MV'] = np.abs(crsp['PRC']) * crsp['SHROUT']
crsp['RET'] *= 100
crsp
```

[3]:	PERMNO	date	SHRCD	EXCHCD	PRC	RET	SHROUT	year	\
2	10000	1986-02	10	3	-3.25000	-25.7143	3680.0	1986	
3	10000	1986-03	10	3	-4.43750	36.5385	3680.0	1986	
4	10000	1986-04	10	3	-4.00000	-9.8592	3793.0	1986	
5	10000	1986-05	10	3	-3.10938	-22.2656	3793.0	1986	
6	10000	1986-06	10	3	-3.09375	-0.5025	3793.0	1986	
...	...	...	...	...	...	...	...	...	
4705164	93436	2020-08	11	3	498.32001	74.1452	931809.0	2020	
4705165	93436	2020-09	11	3	429.01001	-13.9087	948000.0	2020	
4705166	93436	2020-10	11	3	388.04001	-9.5499	947901.0	2020	
4705167	93436	2020-11	11	3	567.59998	46.2736	947901.0	2020	
4705168	93436	2020-12	11	3	705.66998	24.3252	959854.0	2020	
MV									
2	1.196000e+04								
3	1.633000e+04								
4	1.517200e+04								

```

5          1.179388e+04
6          1.173459e+04
...
4705164    4.643391e+08
4705165    4.067015e+08
4705166    3.678235e+08
4705167    5.380286e+08
4705168    6.773402e+08

```

[3563041 rows x 9 columns]

```

[4]: '''
Load FF5 and Industries data
'''

ff5 = pd.read_csv('ff5_factors.csv')
ff5 = ff5.astype({'date': 'string'})
ff5['date'] = ff5['date'].apply(lambda x: x[:4] + '-' + x[4:])

mom = pd.read_csv('F-F_Momentum_Factor.CSV')
mom = mom.astype({'date': 'string'})
mom['date'] = mom['date'].apply(lambda x: x[:4] + '-' + x[4:])

ff5_mom = pd.merge(ff5, mom, on='date', how='inner')
assert len(ff5_mom) == len(ff5)
ff5_mom

```

```

[4]:
      date  Mkt-RF  SMB  HML  RMW  CMA  RF  MOM
0  1963-07   -0.39 -0.41 -0.97  0.68 -1.18  0.27  0.90
1  1963-08    5.07 -0.80  1.80  0.36 -0.35  0.25  1.01
2  1963-09   -1.57 -0.52  0.13 -0.71  0.29  0.27  0.19
3  1963-10    2.53 -1.39 -0.10  2.80 -2.01  0.29  3.12
4  1963-11   -0.85 -0.88  1.75 -0.51  2.24  0.27 -0.74
..
723 2023-10   -3.19 -4.05  0.19  2.46 -0.66  0.47  1.73
724 2023-11    8.84 -0.12  1.64 -3.91 -1.00  0.44  2.75
725 2023-12    4.87  7.32  4.93 -3.07  1.32  0.43 -5.51
726 2024-01    0.71 -5.74 -2.38  0.69 -0.96  0.47  5.18
727 2024-02    5.06 -0.78 -3.48 -1.98 -2.13  0.42  4.92

```

[728 rows x 8 columns]

```

[5]: '''
Load 100 Best Companies to Work for in America
'''

bcw = pd.read_csv('bcwlist_modified.csv')

```

```
bcw = bcw.dropna(subset=['permno'])

# Set types for relevant columns
bcw = bcw.astype({'rank': 'int', 'company': 'string', 'year': 'int'})
bcw.rename(columns={'permno': 'PERMNO'}, inplace=True)
bcw = bcw.sort_values(by=['year', 'rank'])
bcw
```

```
[5]:
```

	rank	company	PERMNO	year
0	1	AT&T Bell Laboratories	66093.0	1984
1	2	Trammell Crow Company	85629.0	1984
2	3	Delta Airlines	26112.0	1984
3	4	Federal Express	60628.0	1984
4	5	Goldman Sachs	86868.0	1984
...	...	...	...	...
2486	87	AbbVie	13721.0	2020
2487	88	Encompass Home Health & Hospice	10693.0	2020
2493	94	Goldman Sachs	86868.0	2020
2498	99	Delta Airlines	91926.0	2020
2499	100	Four Seasons Hotels	84592.0	2020

[1329 rows x 4 columns]

## 1.2 Problem 1

### 1.2.1 Part A - Process

**Data cleaning:** \* Filter CRSP to ordinary/common shares (SHRCD = 10 or 11) and NYSE, AMEX, and NASDAQ stocks (EXCHCD = 1, 2, or 3)] \* Do not filter out CRSP negative prices. We only need the estimates of return data. \* Assume that if no BCW PERMNO then not publicly traded and remove from dataset \* Augment bcw dataframe with all years a portfolio will be active. For example, the portfolio formed in 1984 is active in 1985, 1986, ... 1992.

**Calculating weights:** \* Merge CRSP data with bcw dataframe on year, so that monthly price data for all stocks in an active best companies portfolio are present \* Create **rebalance column**: True if rebalancing based on stock prices that month, false otherwise. Rebalancing is true iff it is January the year the portfolio was formed or a stock is listed or delisted in that month. \* Apply `calc_weights`, which rebalances the entire portfolio if rebalancing == True, and if not returns NaN weights. \* After sorting by PERMNO and date Fill NaN weights with the first non-NaN weights above them, keeping the weights the same for months where we don't rebalance the portfolio. One stock's weights can never be filled with the weights of another since the earliest date of any stock always has rebalance == True \* Pad all stocks that are de-listed at any time(s) with an extra month of 0 returns \* Shift weights down by one date for each stock. For de-listing months, the previous month's weights occupy the padded month as desired, since the portfolio will carry the stock with 0 returns during the month it is de-listed, then be updated next month. For listing months, the weights from the first month the stock is present are shifted down to form the portfolio for the next month

**Calculating returns:** \* As in HW2, multiply the returns of each stock with its lagged weights,

which are the weights the portfolio started that month with

```
[6]: # Prepare bcw for merge by adding years between 1984 - 1993, 1993 - 1998
bcw['year_formed'] = bcw['year']

bcw_extra = []
for year_formed, gap_length in zip([1984, 1993], [1993 - 1984, 1998 - 1993]):
    to_increment = bcw[bcw['year_formed'] == year_formed]
    for increment in range(1, gap_length):
        for _, row in to_increment.iterrows():
            row['year'] += increment
            bcw_extra.append(row.to_dict())

bcw_extra = pd.DataFrame(bcw_extra, columns=bcw.columns)
bcw = pd.concat([bcw, bcw_extra], ignore_index=True)
bcw
```

```
[6]:
```

	rank	company	PERMNO	year	year_formed
0	1	AT&T Bell Laboratories	66093.0	1984	1984
1	2	Trammell Crow Company	85629.0	1984	1984
2	3	Delta Airlines	26112.0	1984	1984
3	4	Federal Express	60628.0	1984	1984
4	5	Goldman Sachs	86868.0	1984	1984
...	...	...	...	...	...
2320	101	Viking Freight System	80814.0	1997	1993
2321	101	Wal-Mart Stores	55976.0	1997	1993
2322	101	Weyerhaeuser Company	39917.0	1997	1993
2323	101	Worthington Industries	83601.0	1997	1993
2324	101	Xerox	27983.0	1997	1993

[2325 rows x 5 columns]

```
[7]: # Merge bcw and crsp
df = pd.merge(bcw, crsp, how='inner', on=['year', 'PERMNO'])
df = df.sort_values(by=['PERMNO', 'date'])

# Find dates where firms were listed and de-listed
special_dates = set(df.groupby('PERMNO')['date'].min().tolist())
last_trade_dates = df.groupby('PERMNO')['date'].max().tolist()
for date in last_trade_dates:
    special_dates.add(get_next_month_str(date))

# Add to special dates if any firms are de-listed then listed again
prev_row = df.iloc[0]
for _, row in df.iloc[1:].iterrows():
    if (not is_next_month(prev_row['date'], row['date'])) and_
    ↪(prev_row['PERMNO'] == row['PERMNO']):
```

```

        special_dates.add(get_next_month_str(prev_row['date']))
        special_dates.add(row['date'])
    prev_row = row

# Add rebalance column -- rebalance if its January when the portfolio was
formed or if its a special date
df['rebalance'] = (df['date'].str[-2:] == '01') | (df['date'].
    isin(special_dates))

df = df.drop(['rank', 'SHRCD', 'EXCHCD', 'PRC', 'SHROUT'], axis=1)
df = df.sort_values(by=['date'])
df

```

```

[7]:

```

	company	PERMNO	year	year_formed	\
562	Moog	61807.0	1984	1984	
394	Inland Steel Company	12458.0	1984	1984	
490	Liebert Corporation	49411.0	1984	1984	
154	Armstrong	19692.0	1984	1984	
70	Time	40483.0	1984	1984	
...	...	...	...	...	
13271	Hilton	14338.0	2020	2020	
13379	CarMax	89508.0	2020	2020	
13331	American Express	59176.0	2020	2020	
13391	Capital One Financial	81055.0	2020	2020	
13583	First American Financial Corporation	93374.0	2020	2020	

	date	RET	MV	rebalance
562	1984-01	-15.0000	8.582875e+04	True
394	1984-01	-3.2258	7.469400e+05	True
490	1984-01	1.7857	3.116048e+05	True
154	1984-01	-5.4299	6.469856e+05	True
70	1984-01	-8.9417	2.671005e+06	True
...	...	...	...	...
13271	2020-12	7.3627	3.086864e+07	False
13379	2020-12	1.0483	1.540019e+07	False
13331	2020-12	1.9563	9.735697e+07	False
13391	2020-12	15.4250	4.521369e+07	False
13583	2020-12	7.5351	5.764231e+06	False

[23034 rows x 8 columns]

```

[8]: # Group by date and calculate weights
df_weights = df.groupby('date', group_keys=False).apply(calc_weights)

# Assert that calc_weights is returning weights when rebalance is needed only
assert len(df_weights[(df_weights['rebalance'] == True) & (np.
    isnan(df_weights['weights_eq']))]) == 0

```



```

assert len(df_weights[(df_weights['rebalance'] == True) & (np.
    ↳ isnan(df_weights['weights_val']))]) == 0

# Fill the NaNs returned from calc_weights when there are no rebalances
# using the weights for that PERMNO on the previous date
df_weights = df_weights.sort_values(['PERMNO', 'date'])
df_weights['weights_eq'] = df_weights['weights_eq'].fillna(method='ffill')
df_weights['weights_val'] = df_weights['weights_val'].fillna(method='ffill')

# Pad all stocks with 1 extra month of 0 returns for weight shift
df_weights = df_weights.groupby('PERMNO').apply(add_padding_month).
    ↳ reset_index(drop=True)

# Shift weights
df_weights = df_weights.sort_values(['PERMNO', 'date'])
df_weights['weights_eq_lag'] = df_weights.groupby('PERMNO')['weights_eq'].
    ↳ shift(1)
df_weights['weights_val_lag'] = df_weights.groupby('PERMNO')['weights_val'].
    ↳ shift(1)
df_weights = df_weights.dropna(subset=['weights_eq_lag', 'weights_val_lag'])

# Assert that weights add up to one for all dates
test1 = df_weights.groupby('date')['weights_eq_lag'].sum()
test2 = df_weights.groupby('date')['weights_val_lag'].sum()
assert test1.apply(lambda x: np.isclose(x, 1.0, atol=0.00001)).all()
assert test2.apply(lambda x: np.isclose(x, 1.0, atol=0.00001)).all()

df_weights = df_weights.drop(['year', 'MV'], axis=1)
df_weights = df_weights.sort_values(['date', 'PERMNO'])
df_weights

```

```

[8]:
      company  PERMNO  year_formed  date \
402  Atlantic Richfield Company  10604.0  1984.0  1984-02
710      Dana Corporation  11607.0  1984.0  1984-02
893      Du Pont  11703.0  1984.0  1984-02
1062  Eastman Kodak Company  11754.0  1984.0  1984-02
1171  Exxon Corporation  11850.0  1984.0  1984-02
...
22660  Salesforce.com  90215.0  NaN  2021-01
23068  Delta Airlines  91926.0  NaN  2021-01
23105  T-Mobile US  91937.0  NaN  2021-01
23305  Hyatt Hotels Corporation  93098.0  NaN  2021-01
23366  First American Financial Corporation  93374.0  NaN  2021-01

      RET  rebalance  weights_eq  weights_val  weights_eq_lag \
402   -0.5525    False   0.014085   0.038332   0.014085
710  -13.3739    False   0.014085   0.005508   0.014085

```

893	-3.3668	False	0.014085	0.040308	0.014085
1062	-5.8319	False	0.014085	0.040958	0.014085
1171	-1.1321	False	0.014085	0.114076	0.014085
...	...	...	...	...	...
22660	0.0000	<NA>	NaN	NaN	0.029412
23068	0.0000	<NA>	NaN	NaN	0.029412
23105	0.0000	<NA>	NaN	NaN	0.029412
23305	0.0000	<NA>	NaN	NaN	0.029412
23366	0.0000	<NA>	NaN	NaN	0.029412

	weights_val_lag
402	0.038332
710	0.005508
893	0.040308
1062	0.040958
1171	0.114076
...	...
22660	0.085811
23068	0.019130
23105	0.036010
23305	0.001641
23366	0.003695

[23034 rows x 10 columns]

## 1.3 Problem 2

### 1.3.1 Part A

```
[9]: # Add returns
df_weights['weighted_eq_ret'] = df_weights['weights_eq_lag'] * df_weights['RET']
df_weights['weighted_val_ret'] = df_weights['weights_val_lag'] *
    ↪df_weights['RET']

eq_returns = df_weights.groupby('date')['weighted_eq_ret'].sum()
val_returns = df_weights.groupby('date')['weighted_val_ret'].sum()

analyze(eq_returns, "Equal-weighted Best Companies")
print()
analyze(val_returns, "Value-weighted Best Companies")
```

Equal-weighted Best Companies monthly returns:

Mean = 1.220920902080068%

Volatility = 5.403471378171253%

Sharpe Ratio = 0.22595121110704866

Value-weighted Best Companies monthly returns:

Mean = 1.0771412191404004%

Volatility = 5.264385220495521%  
 Sharpe Ratio = 0.20460911844878485

### 1.3.2 Part B

```
[10]: eq_capm_beta = estimate_models(eq_returns, 'weighted_eq_ret', ff5_mom)
```

CAPM

OLS Regression Results						
=====						
Dep. Variable:	y	R-squared:	0.892			
Model:	OLS	Adj. R-squared:	0.892			
Method:	Least Squares	F-statistic:	3653.			
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	8.79e-216			
Time:	10:59:49	Log-Likelihood:	-885.39			
No. Observations:	444	AIC:	1775.			
Df Residuals:	442	BIC:	1783.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	0.1085	0.086	1.267	0.206	-0.060	0.277
Mkt-RF	1.1413	0.019	60.437	0.000	1.104	1.178
=====						
Omnibus:	58.357	Durbin-Watson:	1.962			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	168.101			
Skew:	0.615	Prob(JB):	3.14e-37			
Kurtosis:	5.752	Cond. No.	4.60			
-----						

Notes:

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

FF3

OLS Regression Results						
=====						
Dep. Variable:	y	R-squared:	0.901			
Model:	OLS	Adj. R-squared:	0.900			
Method:	Least Squares	F-statistic:	1334.			
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	1.93e-220			
Time:	10:59:49	Log-Likelihood:	-866.28			
No. Observations:	444	AIC:	1741.			
Df Residuals:	440	BIC:	1757.			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.1105	0.082	1.340	0.181	-0.052	0.272
Mkt-RF	1.1183	0.019	59.270	0.000	1.081	1.155
SMB	0.1755	0.028	6.205	0.000	0.120	0.231
HML	0.0325	0.028	1.167	0.244	-0.022	0.087
=====						
Omnibus:		66.589	Durbin-Watson:			2.034
Prob(Omnibus):		0.000	Jarque-Bera (JB):			168.211
Skew:		0.749	Prob(JB):			2.97e-37
Kurtosis:		5.617	Cond. No.			4.74
=====						

Notes:

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

Carhart

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.911
Model:	OLS	Adj. R-squared:	0.911
Method:	Least Squares	F-statistic:	1128.
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	2.21e-229
Time:	10:59:49	Log-Likelihood:	-841.73
No. Observations:	444	AIC:	1693.
Df Residuals:	439	BIC:	1714.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.2103	0.079	2.652	0.008	0.054	0.366
Mkt-RF	1.0836	0.019	58.521	0.000	1.047	1.120
SMB	0.1743	0.027	6.504	0.000	0.122	0.227
HML	-0.0177	0.027	-0.649	0.517	-0.071	0.036
MOM	-0.1299	0.018	-7.165	0.000	-0.165	-0.094

Omnibus:	30.015	Durbin-Watson:	2.080
Prob(Omnibus):	0.000	Jarque-Bera (JB):	59.713
Skew:	0.397	Prob(JB):	1.08e-13
Kurtosis:	4.612	Cond. No.	5.19

Notes:

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

FF5

#### OLS Regression Results

```

Dep. Variable:          y      R-squared:          0.905
Model:                  OLS    Adj. R-squared:       0.904
Method:                 Least Squares  F-statistic:       836.2
Date:                  Fri, 26 Apr 2024  Prob (F-statistic): 1.87e-221
Time:                  10:59:49  Log-Likelihood:    -856.62
No. Observations:      444      AIC:              1725.
Df Residuals:          438      BIC:              1750.
Df Model:              5
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.1057	0.084	1.254	0.210	-0.060	0.271
Mkt-RF	1.1089	0.020	54.639	0.000	1.069	1.149
SMB	0.2160	0.030	7.121	0.000	0.156	0.276
HML	0.0760	0.037	2.056	0.040	0.003	0.149
RMW	0.1123	0.040	2.831	0.005	0.034	0.190
CMA	-0.1696	0.057	-2.998	0.003	-0.281	-0.058
Omnibus:		53.301	Durbin-Watson:		2.037	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		103.410	
Skew:		0.692	Prob(JB):		3.51e-23	
Kurtosis:		4.917	Cond. No.		5.30	

Notes:

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

```
[11]: val_capm_beta = estimate_models(val_returns, 'weighted_val_ret', ff5_mom)
```

CAPM

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.834			
Model:	OLS	Adj. R-squared:	0.834			
Method:	Least Squares	F-statistic:	2220.			
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	1.90e-174			
Time:	10:59:49	Log-Likelihood:	-968.65			
No. Observations:	444	AIC:	1941.			
Df Residuals:	442	BIC:	1949.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	0.0145	0.103	0.140	0.888	-0.189	0.218
Mkt-RF	1.0734	0.023	47.119	0.000	1.029	1.118

```

=====
Omnibus:                27.575    Durbin-Watson:                2.132
Prob(Omnibus):          0.000    Jarque-Bera (JB):          95.506
Skew:                   0.008    Prob(JB):                  1.82e-21
Kurtosis:               5.272    Cond. No.                  4.60
=====

```

Notes:

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

FF3

#### OLS Regression Results

```

=====
Dep. Variable:          y    R-squared:                0.854
Model:                  OLS    Adj. R-squared:          0.853
Method:                  Least Squares    F-statistic:            857.5
Date:                    Fri, 26 Apr 2024    Prob (F-statistic):      2.44e-183
Time:                    10:59:49    Log-Likelihood:          -940.21
No. Observations:        444    AIC:                    1888.
Df Residuals:            440    BIC:                    1905.
Df Model:                 3
Covariance Type:         nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0476	0.097	0.489	0.625	-0.144	0.239
Mkt-RF	1.0705	0.022	48.037	0.000	1.027	1.114
SMB	-0.1398	0.033	-4.185	0.000	-0.206	-0.074
HML	-0.2176	0.033	-6.624	0.000	-0.282	-0.153

```

=====
Omnibus:                18.531    Durbin-Watson:                2.150
Prob(Omnibus):          0.000    Jarque-Bera (JB):          44.123
Skew:                   0.108    Prob(JB):                  2.62e-10
Kurtosis:               4.529    Cond. No.                  4.74
=====

```

Notes:

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

Carhart

#### OLS Regression Results

```

=====
Dep. Variable:          y    R-squared:                0.860
Model:                  OLS    Adj. R-squared:          0.859
Method:                  Least Squares    F-statistic:            676.3
Date:                    Fri, 26 Apr 2024    Prob (F-statistic):      3.94e-186
Time:                    10:59:49    Log-Likelihood:          -930.20
No. Observations:        444    AIC:                    1870.

```

Df Residuals: 439 BIC: 1891.  
Df Model: 4  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.1242	0.097	1.283	0.200	-0.066	0.314
Mkt-RF	1.0440	0.023	46.194	0.000	1.000	1.088
SMB	-0.1408	0.033	-4.304	0.000	-0.205	-0.077
HML	-0.2561	0.033	-7.695	0.000	-0.322	-0.191
MOM	-0.0995	0.022	-4.500	0.000	-0.143	-0.056
Omnibus:	18.601	Durbin-Watson:	2.114			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	39.714			
Skew:	0.182	Prob(JB):	2.38e-09			
Kurtosis:	4.419	Cond. No.	5.19			

Notes:

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

FF5

#### OLS Regression Results

Dep. Variable: y R-squared: 0.862  
Model: OLS Adj. R-squared: 0.860  
Method: Least Squares F-statistic: 545.1  
Date: Fri, 26 Apr 2024 Prob (F-statistic): 1.74e-185  
Time: 10:59:49 Log-Likelihood: -928.33  
No. Observations: 444 AIC: 1869.  
Df Residuals: 438 BIC: 1893.  
Df Model: 5  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.1651	0.099	1.667	0.096	-0.030	0.360
Mkt-RF	1.0239	0.024	42.925	0.000	0.977	1.071
SMB	-0.1558	0.036	-4.370	0.000	-0.226	-0.086
HML	-0.0747	0.043	-1.720	0.086	-0.160	0.011
RMW	-0.0839	0.047	-1.800	0.073	-0.176	0.008
CMA	-0.3162	0.066	-4.757	0.000	-0.447	-0.186
Omnibus:	17.214	Durbin-Watson:	2.149			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	33.321			
Skew:	0.201	Prob(JB):	5.81e-08			
Kurtosis:	4.280	Cond. No.	5.30			

Notes:

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

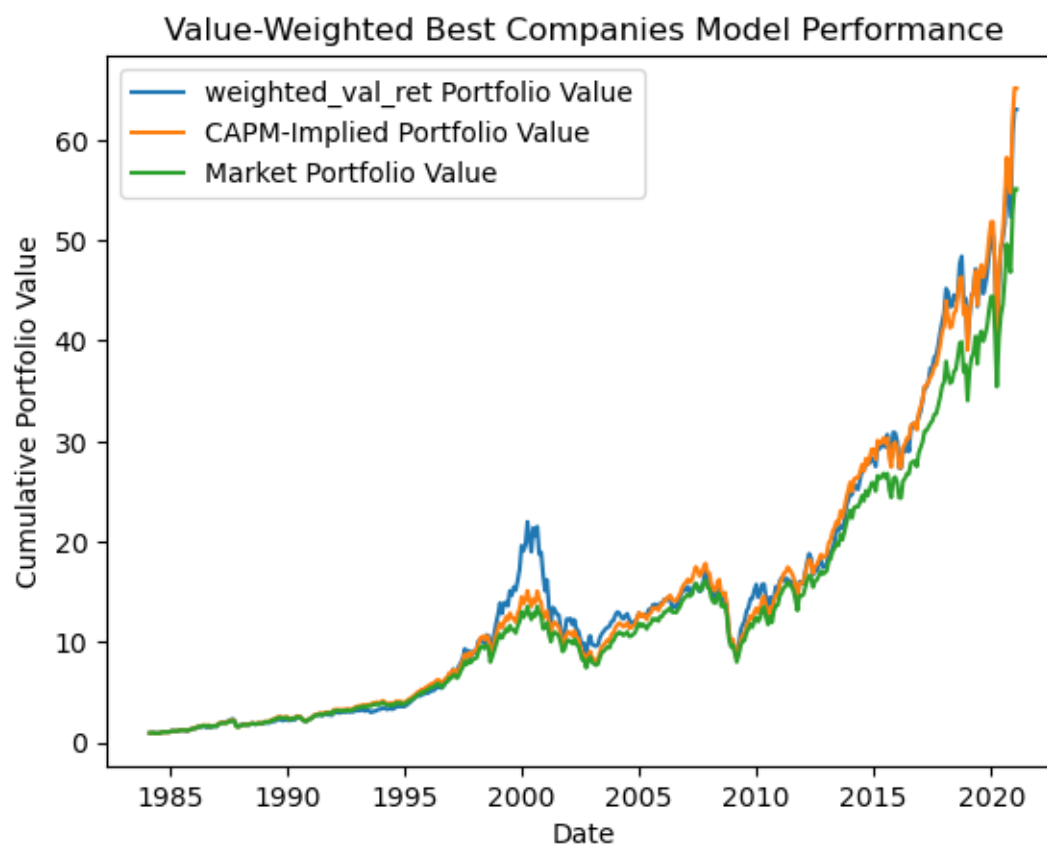
The equal-weighted produces positive alphas, but the alphas are insignificant except under the Carhart model, where they are significant at the 1% level. The value-weighted portfolios produce positive insignificant alphas, except under the FF5 model, where they are significant at the 10% level.

### 1.3.3 Part C

```
[12]: val_ff5 = pd.merge(val_returns.to_frame(), ff5, how='inner', on=['date'])
      assert len(val_ff5) == len(val_returns)

      val_ff5['date'] = (val_ff5['date'].str[:4] + val_ff5['date'].str[5:]).
        ↳astype('int')

      plot_cum_returns(val_ff5, 'weighted_val_ret', val_capm_beta, 'Value-Weighted_
        ↳Best Companies')
```





The value-weighted Best Companies strategy is highly correlated to the market portfolio, which makes sense given its beta of 1.02. It performs almost the exact same as the CAPM model implied returns. Interestingly, the strategy outperforms the CAPM model in the late 1990's, but in the early 2000's loses all of those gains and remains roughly the same as the CAPM model.

### 1.3.4 Part D

```
[13]: eq_returns_pre_jan1 = eq_returns[eq_returns.index < '2010-01']
eq_returns_post_jan1 = eq_returns[eq_returns.index >= '2010-01']

val_returns_pre_jan1 = val_returns[val_returns.index < '2010-01']
val_returns_post_jan1 = val_returns[val_returns.index >= '2010-01']

[14]: estimate_models(eq_returns_pre_jan1, 'weighted_eq_ret', ff5_mom)
```

CAPM

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                  0.894
Model:                        OLS      Adj. R-squared:             0.893
Method:                    Least Squares  F-statistic:                2599.
Date:                Fri, 26 Apr 2024  Prob (F-statistic):        1.84e-152
Time:                10:59:49      Log-Likelihood:            -624.62
No. Observations:          311      AIC:                        1253.
Df Residuals:              309      BIC:                        1261.
Df Model:                   1
Covariance Type:            nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.1791      0.103        1.733      0.084      -0.024      0.382
Mkt-RF         1.1456      0.022       50.976      0.000        1.101      1.190
=====
Omnibus:                    59.444  Durbin-Watson:                1.821
Prob(Omnibus):              0.000  Jarque-Bera (JB):            141.583
Skew:                      0.924  Prob(JB):                    1.80e-31
Kurtosis:                   5.741  Cond. No.                     4.63
=====
```

Notes:

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

FF3

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                  0.904
Model:                        OLS      Adj. R-squared:             0.903
Method:                    Least Squares  F-statistic:                958.8
```

Date: Fri, 26 Apr 2024 Prob (F-statistic): 1.62e-155  
Time: 10:59:49 Log-Likelihood: -609.52  
No. Observations: 311 AIC: 1227.  
Df Residuals: 307 BIC: 1242.  
Df Model: 3  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.1526	0.100	1.529	0.127	-0.044	0.349
Mkt-RF	1.1378	0.023	50.282	0.000	1.093	1.182
SMB	0.1791	0.033	5.508	0.000	0.115	0.243
HML	0.0612	0.034	1.804	0.072	-0.006	0.128
Omnibus:	57.788	Durbin-Watson:	1.917			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	134.842			
Skew:	0.907	Prob(JB):	5.24e-30			
Kurtosis:	5.668	Cond. No.	4.88			

Notes:

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

Carhart

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.919			
Model:	OLS	Adj. R-squared:	0.918			
Method:	Least Squares	F-statistic:	872.8			
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	6.41e-166			
Time:	10:59:49	Log-Likelihood:	-581.59			
No. Observations:	311	AIC:	1173.			
Df Residuals:	306	BIC:	1192.			
Df Model:	4					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	0.2899	0.093	3.115	0.002	0.107	0.473
Mkt-RF	1.0944	0.021	51.007	0.000	1.052	1.137
SMB	0.1800	0.030	6.045	0.000	0.121	0.239
HML	0.0041	0.032	0.127	0.899	-0.059	0.067
MOM	-0.1495	0.019	-7.760	0.000	-0.187	-0.112
=====						
Omnibus:	22.918	Durbin-Watson:	1.952			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	42.241			
Skew:	0.427	Prob(JB):	6.72e-10			
Kurtosis:	4.591	Cond. No.	5.44			

Notes:

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

FF5

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.906
Model:                  OLS    Adj. R-squared:      0.904
Method:                 Least Squares  F-statistic:    588.2
Date:                   Fri, 26 Apr 2024  Prob (F-statistic): 2.93e-154
Time:                   10:59:49  Log-Likelihood:  -605.47
No. Observations:      311      AIC:             1223.
Df Residuals:          305      BIC:             1245.
Df Model:               5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.1107	0.103	1.071	0.285	-0.093	0.314
Mkt-RF	1.1443	0.025	45.291	0.000	1.095	1.194
SMB	0.2177	0.035	6.184	0.000	0.148	0.287
HML	0.0601	0.046	1.308	0.192	-0.030	0.151
RMW	0.1124	0.045	2.485	0.013	0.023	0.201
CMA	-0.0601	0.067	-0.893	0.373	-0.193	0.072

```
=====
Omnibus:                47.746  Durbin-Watson:          1.915
Prob(Omnibus):           0.000  Jarque-Bera (JB):        95.887
Skew:                    0.809  Prob(JB):                1.51e-21
Kurtosis:                5.186  Cond. No.                 5.63
=====
```

Notes:

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

[14]: 1.1456255645790132

[15]: `estimate_models(val_returns_pre_jan1, 'weighted_val_ret', ff5_mom)`

CAPM

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.823
Model:                  OLS    Adj. R-squared:      0.822
Method:                 Least Squares  F-statistic:    1436.
Date:                   Fri, 26 Apr 2024  Prob (F-statistic): 3.57e-118
=====
```

Time: 10:59:49 Log-Likelihood: -696.81  
 No. Observations: 311 AIC: 1398.  
 Df Residuals: 309 BIC: 1405.  
 Df Model: 1  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0763	0.130	0.585	0.559	-0.180	0.333
Mkt-RF	1.0740	0.028	37.890	0.000	1.018	1.130
Omnibus:	22.393		Durbin-Watson:	2.081		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	78.564		
Skew:	-0.051		Prob(JB):	8.71e-18		
Kurtosis:	5.460		Cond. No.	4.63		

Notes:

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

FF3

#### OLS Regression Results

Dep. Variable: y R-squared: 0.857  
 Model: OLS Adj. R-squared: 0.856  
 Method: Least Squares F-statistic: 613.9  
 Date: Fri, 26 Apr 2024 Prob (F-statistic): 2.50e-129  
 Time: 10:59:49 Log-Likelihood: -663.40  
 No. Observations: 311 AIC: 1335.  
 Df Residuals: 307 BIC: 1350.  
 Df Model: 3  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.2108	0.119	1.777	0.077	-0.023	0.444
Mkt-RF	1.0325	0.027	38.371	0.000	0.980	1.085
SMB	-0.1836	0.039	-4.749	0.000	-0.260	-0.108
HML	-0.3140	0.040	-7.778	0.000	-0.393	-0.235
Omnibus:	18.769		Durbin-Watson:	2.069		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	43.759		
Skew:	0.245		Prob(JB):	3.15e-10		
Kurtosis:	4.771		Cond. No.	4.88		

Notes:

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

specified.

Carhart

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.866
Model:                  OLS    Adj. R-squared:      0.864
Method:                 Least Squares  F-statistic:    493.7
Date:                  Fri, 26 Apr 2024  Prob (F-statistic):  4.50e-132
Time:                  10:59:49  Log-Likelihood:   -653.62
No. Observations:      311      AIC:            1317.
Df Residuals:          306      BIC:            1336.
Df Model:              4
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.3103	0.117	2.645	0.009	0.079	0.541
Mkt-RF	1.0011	0.027	37.012	0.000	0.948	1.054
SMB	-0.1830	0.038	-4.876	0.000	-0.257	-0.109
HML	-0.3554	0.040	-8.825	0.000	-0.435	-0.276
MOM	-0.1082	0.024	-4.457	0.000	-0.156	-0.060

```
=====
Omnibus:                17.969  Durbin-Watson:      2.034
Prob(Omnibus):          0.000  Jarque-Bera (JB):    32.544
Skew:                   0.334  Prob(JB):            8.57e-08
Kurtosis:               4.437  Cond. No.            5.44
=====
```

Notes:

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

FF5

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.862
Model:                  OLS    Adj. R-squared:      0.859
Method:                 Least Squares  F-statistic:    379.5
Date:                  Fri, 26 Apr 2024  Prob (F-statistic):  1.33e-128
Time:                  10:59:49  Log-Likelihood:   -658.55
No. Observations:      311      AIC:            1329.
Df Residuals:          305      BIC:            1352.
Df Model:              5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.3123	0.123	2.546	0.011	0.071	0.554
Mkt-RF	0.9899	0.030	33.031	0.000	0.931	1.049

SMB	-0.2018	0.042	-4.834	0.000	-0.284	-0.120
HML	-0.1985	0.055	-3.642	0.000	-0.306	-0.091
RMW	-0.0888	0.054	-1.655	0.099	-0.194	0.017
CMA	-0.2309	0.080	-2.891	0.004	-0.388	-0.074

Omnibus:	18.423	Durbin-Watson:	2.054
Prob(Omnibus):	0.000	Jarque-Bera (JB):	36.181
Skew:	0.312	Prob(JB):	1.39e-08
Kurtosis:	4.550	Cond. No.	5.63

Notes:

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

[15]: 1.07400676934913

[16]: estimate\_models(eq\_returns\_post\_jan1, 'weighted\_eq\_ret', ff5\_mom)

CAPM

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.888
Model:	OLS	Adj. R-squared:	0.888
Method:	Least Squares	F-statistic:	1043.
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	2.98e-64
Time:	10:59:49	Log-Likelihood:	-259.57
No. Observations:	133	AIC:	523.1
Df Residuals:	131	BIC:	528.9
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0552	0.154	-0.358	0.721	-0.361	0.250
Mkt-RF	1.1356	0.035	32.303	0.000	1.066	1.205

Omnibus:	12.646	Durbin-Watson:	2.328
Prob(Omnibus):	0.002	Jarque-Bera (JB):	28.717
Skew:	-0.293	Prob(JB):	5.81e-07
Kurtosis:	5.200	Cond. No.	4.58

Notes:

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

FF3

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.898
Model:                        OLS    Adj. R-squared:           0.895
Method:                       Least Squares  F-statistic:             377.2
Date:                         Fri, 26 Apr 2024  Prob (F-statistic):    1.22e-63
Time:                         10:59:49    Log-Likelihood:          -253.85
No. Observations:            133    AIC:                     515.7
Df Residuals:                129    BIC:                     527.3
Df Model:                    3
Covariance Type:              nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0314	0.153	-0.206	0.837	-0.333	0.271
Mkt-RF	1.0845	0.038	28.728	0.000	1.010	1.159
SMB	0.2192	0.065	3.397	0.001	0.092	0.347
HML	-0.0465	0.058	-0.798	0.426	-0.162	0.069

```

=====
Omnibus:                    10.516    Durbin-Watson:           2.414
Prob(Omnibus):              0.005    Jarque-Bera (JB):        25.784
Skew:                       -0.073    Prob(JB):                2.52e-06
Kurtosis:                   5.152    Cond. No.                4.95
=====

```

Notes:

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

Carhart

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.898
Model:                        OLS    Adj. R-squared:           0.895
Method:                       Least Squares  F-statistic:             281.5
Date:                         Fri, 26 Apr 2024  Prob (F-statistic):    2.16e-62
Time:                         10:59:49    Log-Likelihood:          -253.67
No. Observations:            133    AIC:                     517.3
Df Residuals:                128    BIC:                     531.8
Df Model:                    4
Covariance Type:              nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0230	0.154	-0.150	0.881	-0.327	0.281
Mkt-RF	1.0798	0.039	27.913	0.000	1.003	1.156
SMB	0.2169	0.065	3.346	0.001	0.089	0.345
HML	-0.0597	0.063	-0.954	0.342	-0.184	0.064
MOM	-0.0284	0.048	-0.589	0.557	-0.124	0.067

Omnibus:	10.864	Durbin-Watson:	2.415
Prob(Omnibus):	0.004	Jarque-Bera (JB):	27.365
Skew:	-0.080	Prob(JB):	1.14e-06
Kurtosis:	5.216	Cond. No.	5.26

=====

Notes:

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

FF5

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.916
Model:	OLS	Adj. R-squared:	0.913
Method:	Least Squares	F-statistic:	276.7
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	1.78e-66
Time:	10:59:49	Log-Likelihood:	-240.77
No. Observations:	133	AIC:	493.5
Df Residuals:	127	BIC:	510.9
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0539	0.141	0.382	0.703	-0.225	0.333
Mkt-RF	1.0504	0.035	29.920	0.000	0.981	1.120
SMB	0.2615	0.064	4.111	0.000	0.136	0.387
HML	0.1160	0.063	1.827	0.070	-0.010	0.242
RMW	0.1714	0.092	1.868	0.064	-0.010	0.353
CMA	-0.5059	0.104	-4.876	0.000	-0.711	-0.301

Omnibus:	5.555	Durbin-Watson:	2.399
Prob(Omnibus):	0.062	Jarque-Bera (JB):	5.417
Skew:	0.350	Prob(JB):	0.0666
Kurtosis:	3.698	Cond. No.	5.14

=====

Notes:

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

[16]: 1.135639057256818

[17]: estimate\_models(val\_returns\_post\_jan1, 'weighted\_val\_ret', ff5\_mom)

CAPM

#### OLS Regression Results



```

Dep. Variable:          y      R-squared:          0.866
Model:                  OLS    Adj. R-squared:       0.865
Method:                 Least Squares  F-statistic:       844.6
Date:                  Fri, 26 Apr 2024  Prob (F-statistic): 5.71e-59
Time:                  10:59:49  Log-Likelihood:    -266.55
No. Observations:      133     AIC:              537.1
Df Residuals:          131     BIC:              542.9
Df Model:              1
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1346	0.163	-0.827	0.410	-0.457	0.187
Mkt-RF	1.0767	0.037	29.062	0.000	1.003	1.150
Omnibus:		0.491	Durbin-Watson:		2.275	
Prob(Omnibus):		0.782	Jarque-Bera (JB):		0.462	
Skew:		0.140	Prob(JB):		0.794	
Kurtosis:		2.933	Cond. No.		4.58	

Notes:

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

FF3

#### OLS Regression Results

```

Dep. Variable:          y      R-squared:          0.870
Model:                  OLS    Adj. R-squared:       0.867
Method:                 Least Squares  F-statistic:       288.3
Date:                  Fri, 26 Apr 2024  Prob (F-statistic): 5.42e-57
Time:                  10:59:49  Log-Likelihood:    -264.29
No. Observations:      133     AIC:              536.6
Df Residuals:          129     BIC:              548.1
Df Model:              3
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1888	0.165	-1.144	0.255	-0.515	0.138
Mkt-RF	1.1140	0.041	27.281	0.000	1.033	1.195
SMB	-0.1162	0.070	-1.665	0.098	-0.254	0.022
HML	-0.0469	0.063	-0.744	0.458	-0.172	0.078
Omnibus:		0.648	Durbin-Watson:		2.284	
Prob(Omnibus):		0.723	Jarque-Bera (JB):		0.487	
Skew:		0.148	Prob(JB):		0.784	
Kurtosis:		3.024	Cond. No.		4.95	

Notes:

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

Carhart

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.872
Model:                  OLS    Adj. R-squared:      0.868
Method:                 Least Squares  F-statistic:    217.6
Date:                  Fri, 26 Apr 2024  Prob (F-statistic): 4.59e-56
Time:                  10:59:49  Log-Likelihood:  -263.47
No. Observations:      133     AIC:             536.9
Df Residuals:          128     BIC:             551.4
Df Model:               4
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1694	0.165	-1.024	0.308	-0.497	0.158
Mkt-RF	1.1032	0.042	26.490	0.000	1.021	1.186
SMB	-0.1216	0.070	-1.742	0.084	-0.260	0.016
HML	-0.0771	0.067	-1.145	0.254	-0.210	0.056
MOM	-0.0650	0.052	-1.255	0.212	-0.168	0.038

```
=====
Omnibus:                0.459  Durbin-Watson:      2.267
Prob(Omnibus):          0.795  Jarque-Bera (JB):    0.327
Skew:                   0.121  Prob(JB):            0.849
Kurtosis:               3.014  Cond. No.            5.26
=====
```

Notes:

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

FF5

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.892
Model:                  OLS    Adj. R-squared:      0.888
Method:                 Least Squares  F-statistic:    210.3
Date:                  Fri, 26 Apr 2024  Prob (F-statistic): 1.22e-59
Time:                  10:59:49  Log-Likelihood:  -251.93
No. Observations:      133     AIC:             515.9
Df Residuals:          127     BIC:             533.2
Df Model:               5
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
-----	-----	-----	-----	-----	-----	-----
const	-0.0739	0.153	-0.482	0.631	-0.377	0.230
Mkt-RF	1.0790	0.038	28.261	0.000	1.003	1.155
SMB	-0.1331	0.069	-1.924	0.057	-0.270	0.004
HML	0.1444	0.069	2.091	0.038	0.008	0.281
RMW	-0.0546	0.100	-0.547	0.585	-0.252	0.143
CMA	-0.5724	0.113	-5.072	0.000	-0.796	-0.349
=====	=====	=====	=====	=====	=====	=====
Omnibus:		0.982	Durbin-Watson:			2.447
Prob(Omnibus):		0.612	Jarque-Bera (JB):			0.614
Skew:		0.136	Prob(JB):			0.736
Kurtosis:		3.191	Cond. No.			5.14
=====	=====	=====	=====	=====	=====	=====

Notes:

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

[17]: 1.0767224921961434

The strategy worked well before January 1st, 2010. The alphas were positive for the equal and value weighted strategies, and statistically significant at the 1% level when tested using the Carhart model. The alphas and their significance levels, as well as the factor coefficients, are extremely similar to Table 3 in the Edmands paper.

The strategy does not work in the post-period, and has negative alphas under both strategies and all models with the exception of the equal weighted portfolio under FF5, which is positive and insignificant. In commentary on Table 4, the Edmands paper argues that higher alphas under the Feb 1998 - Dec 2009 period, after Forbes began publishing the Best Companies list every year, are evidence that reasons other than lack of public information are behind this market misvaluation. The authors suggest the difficulty of incorporating this information into a traditional evaluation model as one possible reason. Perhaps what happened post Jan 2010 is that with increasing competition in the hedge fund industry and advances in automatic sentiment analysis and online information (ex, Problem 3d), evaluation models got more advanced and were able price employee sentiment more effectively.

### 1.3.5 Part E

```
[18]: '''
Load Industry portfolio data from Ken French's website. Using monthly_
value-weighted industry portfolios.
'''

industries = pd.read_csv('12_Industry_Portfolios.CSV')
industries = industries.astype({'date': 'string'})
industries['date'] = industries['date'].apply(lambda x: x[:4] + '-' + x[4:])
industries
```

```

val_returns_pre_1999 = val_returns[val_returns.index < '1999-01']
val_returns_post_1999 = val_returns[val_returns.index >= '1999-01']

df_pre = pd.merge(industries, val_returns_pre_1999, on=["date"], how="inner")
df_pre = pd.merge(df_pre, ff5_mom, on=["date"], how="inner")
assert len(df_pre) == len(val_returns_pre_1999)

df_post = pd.merge(industries, val_returns_post_1999, on=["date"], how="inner")
df_post = pd.merge(df_post, ff5_mom, on=["date"], how="inner")
assert len(df_post) == len(val_returns_post_1999)

print('Pre-1999')
print(sm.OLS(df_pre['weighted_val_ret'] - df_pre['RF'], sm.
    ↳add_constant(df_pre[['NoDur', 'Durb1', 'Manuf', 'Enrgy', 'Chems', 'BusEq', 'Telcm', 'Utils', 'Shops
    ↳fit()).summary())

print('Post-1999')
print(sm.OLS(df_post['weighted_val_ret'] - df_post['RF'], sm.
    ↳add_constant(df_post[['NoDur', 'Durb1', 'Manuf', 'Enrgy', 'Chems', 'BusEq', 'Telcm', 'Utils', 'Shop
    ↳fit()).summary())

```

Pre-1999

#### OLS Regression Results

=====						
Dep. Variable:	y	R-squared:	0.932			
Model:	OLS	Adj. R-squared:	0.927			
Method:	Least Squares	F-statistic:	189.5			
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	3.62e-90			
Time:	10:59:49	Log-Likelihood:	-291.15			
No. Observations:	179	AIC:	608.3			
Df Residuals:	166	BIC:	649.7			
Df Model:	12					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	-0.4601	0.105	-4.366	0.000	-0.668	-0.252
NoDur	0.1690	0.053	3.162	0.002	0.063	0.275
Durb1	0.0158	0.035	0.447	0.655	-0.054	0.085
Manuf	0.1394	0.082	1.708	0.090	-0.022	0.301
Enrgy	0.1215	0.028	4.354	0.000	0.066	0.177
Chems	0.1616	0.056	2.898	0.004	0.052	0.272
BusEq	0.4446	0.029	15.467	0.000	0.388	0.501
Telcm	0.0604	0.034	1.764	0.080	-0.007	0.128
Utils	-0.0594	0.041	-1.457	0.147	-0.140	0.021
Shops	0.0132	0.045	0.290	0.772	-0.077	0.103

Hlth	0.1453	0.037	3.933	0.000	0.072	0.218
Money	0.0855	0.041	2.094	0.038	0.005	0.166
Other	-0.3550	0.066	-5.388	0.000	-0.485	-0.225

```
=====
Omnibus:                9.461    Durbin-Watson:                2.200
Prob(Omnibus):          0.009    Jarque-Bera (JB):        10.952
Skew:                   0.406    Prob(JB):                0.00419
Kurtosis:               3.899    Cond. No.                17.7
=====
```

Notes:

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

Post-1999

OLS Regression Results

```
=====
Dep. Variable:          y    R-squared:                0.900
Model:                  OLS    Adj. R-squared:         0.896
Method:                 Least Squares    F-statistic:           189.6
Date:                   Fri, 26 Apr 2024    Prob (F-statistic):    1.22e-118
Time:                   10:59:49    Log-Likelihood:        -526.70
No. Observations:       265    AIC:                   1079.
Df Residuals:           252    BIC:                   1126.
Df Model:                12
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1958	0.117	-1.674	0.095	-0.426	0.035
NoDur	0.1078	0.058	1.857	0.064	-0.007	0.222
Durbl	0.0565	0.024	2.378	0.018	0.010	0.103
Manuf	0.0386	0.059	0.652	0.515	-0.078	0.155
Enrgy	0.0409	0.024	1.731	0.085	-0.006	0.087
Chems	0.0097	0.055	0.176	0.861	-0.099	0.119
BusEq	0.5496	0.029	19.191	0.000	0.493	0.606
Telcm	0.0069	0.036	0.192	0.848	-0.064	0.077
Utils	-0.1259	0.035	-3.571	0.000	-0.195	-0.056
Shops	-0.0223	0.047	-0.477	0.634	-0.115	0.070
Hlth	0.1356	0.038	3.600	0.000	0.061	0.210
Money	0.1066	0.039	2.750	0.006	0.030	0.183
Other	0.0089	0.070	0.127	0.899	-0.130	0.147

```
=====
Omnibus:                8.068    Durbin-Watson:                2.239
Prob(Omnibus):          0.018    Jarque-Bera (JB):        12.893
Skew:                   -0.133    Prob(JB):                0.00159
Kurtosis:               4.047    Cond. No.                17.0
=====
```

Notes:

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

Yes, based on the regression it appears that the composition of the best companies to work for has somewhat changed over time. Prior to Jan 1, 1999, the value weighted returns had statistically significant (1%) and sizable positive coefficients ( $>0.1$ ) with the NoDur, Enrgy, Chems, BusEq, and Hlth industries. After Jan 1, 1999, the value weighted returns had statistically significant (1%) and sizable positive coefficients ( $>0.1$ ) with the BusEQ, Utils, Hlth, and Money industries. This indicates that after Jan 1 1999, the Utils and Money industries became better to work for on average, as they became more correlated with our portfolio, while the NoDur, Enrgy and Chems industries got a little worse and the BusEq and Hlth industries remained good to work in, on average.

## 1.4 Problem 3

### 1.4.1 Part A

At around 1.1 for equal-weighted and 1.05 for value-weighted under all four models, the beta of this strategy is very close to 1. Our strategy is long a bundle of specifically selected market assets, which we expect to have a beta of approximately 1 across the board, since we haven't shorted anything or made any explicit selections based on beta value.

With the right weights, a long-short portfolio could be beta neutral, making it more hedged against market risk. This would make it attractive to institutional investors, who are looking for high alpha funds. At the same time, shorting the market portfolio with positive beta would significantly decrease the expected returns of the strategy, making it less attractive to retail investors. It would be interesting to compare the Sharpe Ratio of this new long-short portfolio.

### 1.4.2 Part B

As we can see from the results, estimating the Carhart model from the long portfolio on the best companies to work with (the companies with the highest employee satisfaction) produces a positive alpha that is significant at the 1% level, for both the equal-weighted and value-weighted portfolios. The other three (CAPM, FF3, FF5) models also produce positive alphas, with some significant and some insignificant. Since we were able to generate alpha by simply buying and holding companies that have high employee satisfaction, this shows that financial markets do not fully price the value of employee satisfaction.

### 1.4.3 Part C

One possible reason for why the alpha decreases over time is that people became more aware of this employee satisfaction strategy, and with improvements in automatic sentiment analysis, this became easier to implement at a larger scale (ex, Problem 3d). As more people become aware of the performance of this strategy and start incorporating it more effectively into their own strategies, the efficiencies of the market grow, allowing for financial markets to price the value of employee satisfaction more. This would cause the alpha to decrease over time, decreasing the performance of this strategy.

#### 1.4.4 Part D

Among the many ways in which the employee satisfaction strategy can be improved for the modern world by tracking what employees are reading about in real time, two stand out to us:

Firstly, we can observe the proportion of the time that employees are reading about anything unrelated to their work in general to estimate how distracted employees of a particular company are. Distracted employees would likely be a good indicator of employee disinterest and dissatisfaction and vice versa. Even if distracted employees do not mean that they are disinterested or dissatisfied, it cannot be good for a company's productivity and performance if many of their employees are distracted on the job.

Secondly, we can observe the frequency with which employees browse specific content that indicate dissatisfaction with their job, or about life in general. Employees browsing content related to finding a new job, dealing with their authoritarian boss, improving their depression, etc. with higher than average frequency is a good indication that they are dissatisfied and that their company will underperform.

[ ]: