

# PSS\_BEM\_114\_PS2

April 27, 2024

```
[ ]: import pandas as pd
import statsmodels.api as sm
from statsmodels.regression.rolling import RollingOLS
from sklearn.linear_model import LinearRegression
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.dates import AutoDateLocator, AutoDateFormatter
```

```
[ ]: crsp_data = pd.read_csv("/content/crsp_1926_2020.csv")
```

1A

```
[ ]: crsp_data_filter = crsp_data[crsp_data['SHRCD'].isin([10, 11])]
crsp_data_filter = crsp_data_filter[crsp_data_filter['EXCHCD'].isin([1.0, 2.0, 3.0])]
crsp_data_filter['PRC'] = crsp_data_filter['PRC'].where(crsp_data_filter['PRC'] >= 0)
```

<ipython-input-17-34834b818604>:3: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

```
crsp_data_filter['PRC'] =
crsp_data_filter['PRC'].where(crsp_data_filter['PRC'] >= 0)
```

1B

```
[ ]: dates_df = pd.DataFrame(crsp_data_filter['date'])
dates_df = dates_df.sort_values(by= 'date')

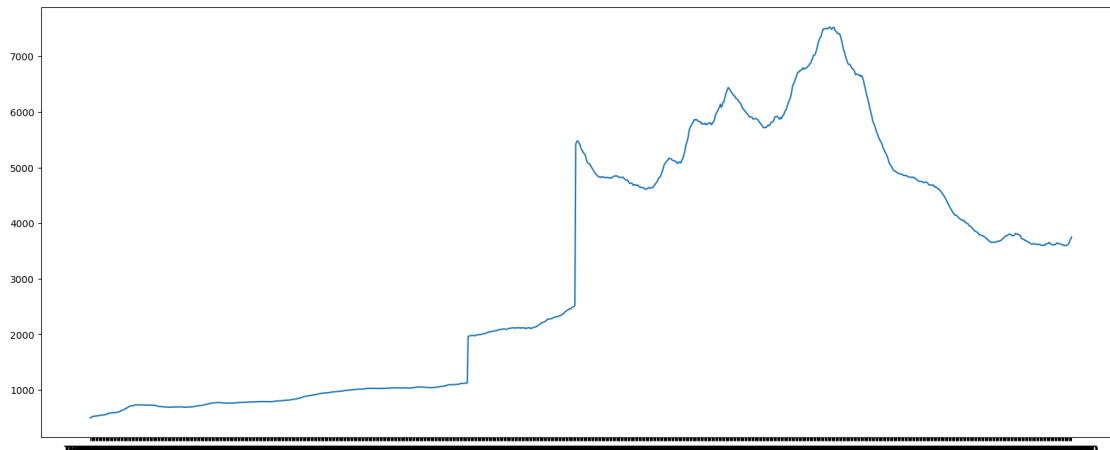
date_list = list(dates_df['date'])
date_set = sorted(set(date_list))

date_dict = {}

for date in date_set:
    date_dict[date] = date_list.count(date)
```

```
[ ]: plt.figure(figsize = (20, 8))
plt.plot(list(date_dict.keys()), list(date_dict.values()))
```

```
[ ]: [<matplotlib.lines.Line2D at 0x7a07d962c700>]
```



```
[ ]: firm_data = pd.read_csv("/content/crsp_1926_2020.csv")
ff5 = pd.read_csv('/content/ff5_factors.csv')
mom_data = pd.read_csv('/content/mom_factor.csv')
```

```
[ ]: firm_data['RET'] = pd.to_numeric(firm_data['RET'], errors='coerce')
firm_data = firm_data.dropna(subset = ['RET'])
firm_data['PRC'] = firm_data['PRC'].where(firm_data['PRC'] >= 0)

data_datemod = firm_data.copy()
data_datemod['date'] = np.floor(data_datemod['date'].str.replace('-', '').
    ↳ astype(float)/100).astype(int)

ff1926 = pd.merge(data_datemod, ff5, how = 'inner', on='date')
ff1926 = pd.merge(ff1926, mom_data, how='inner', on='date')
ff1926.columns = ff1926.columns.str.strip()
data_unique_months = ff1926.drop_duplicates(subset='date', keep='first')
```

```
[ ]: def get_ret(group, decile):
    print("Decile {} mean returns: {}".format(decile, np.mean(group['RET'])))

def print_mean_ret(data):
    print("BY DECILE LAG:")
    data.groupby('decile_lag').apply(lambda x: get_ret(x, x.name))
    print("BY DECILE:")
    data.groupby('decile').apply(lambda x: get_ret(x, x.name))
```

```

def calc_weights(group):
    # Calc equal weights
    group['weights_eq'] = 1 / float(group['decile'].count())
    # Calc total market equity of group
    group['TME'] = group['ME'].sum()
    # Calc value weights
    group['weights_val'] = group['ME'] / group['TME']
    return group

def get_returns(data, split_data, ret_type):
    date_set = sorted(set(data['date']))

    returns = {}

    for date in date_set:
        for i in range(1, 11):
            ret = np.sum(split_data.get_group((float(i), date))[ret_type])
            if i not in returns.keys():
                returns[i] = [ret]
            else:
                returns[i].append(ret)

    return returns

```

```

[ ]: def estim_CAPM(portfolio_ret, data_unique_dates):
    model1 = sm.OLS(portfolio_ret, sm.add_constant(data_unique_dates['Mkt-RF'])).
    ↪fit()
    alpha, beta = model1.params
    print(model1.summary())
    return (beta, alpha)

def estim_FF3(portfolio_ret, data_unique_dates):
    model1=sm.OLS(portfolio_ret, sm.add_constant(data_unique_dates[['Mkt-RF',
    ↪'SMB', 'HML']])).fit()
    alpha, beta_1, beta_2, beta_3 = model1.params
    print(model1.summary())
    return (beta_1, beta_2, beta_3, alpha)

def estim_FF5(portfolio_ret, data_unique_dates):
    model1=sm.OLS(portfolio_ret, sm.add_constant(data_unique_dates[['Mkt-RF',
    ↪'SMB', 'HML', 'RMW', 'CMA']])).fit()
    alpha, beta_1, beta_2, beta_3, beta_4, beta_5 = model1.params
    print(model1.summary())
    return (beta_1, beta_2, beta_3, beta_4, beta_5, alpha)

def estim_FF5mom(portfolio_ret, data_unique_dates):

```

```

model1=sm.OLS(portfolio_ret, sm.add_constant(data_unique_dates[['Mkt-RF',
↪'SMB', 'HML', 'RMW', 'CMA', 'Mom']])).fit()
alpha, beta_1, beta_2, beta_3, beta_4, beta_5, beta_6 = model1.params
print(model1.summary())
return (beta_1, beta_2, beta_3, beta_4, beta_5, beta_6, alpha)

def estim_models(portfolio_ret, ret, data_unique_months):
    mean_ret = np.mean(ret) - 1
    volatility = np.std(ret)
    sharpe_ratio = mean_ret / volatility
    print("Mean returns = {:.3f}".format(mean_ret))
    print("Portfolio volatility = {:.3f}".format(volatility))
    print("Strategy Sharpe Ratio = {:.3f}".format(sharpe_ratio))

    portfolio_ret = [(item - 1) * 100 for item in portfolio_ret]

    # print(portfolio_ret)

    beta, alpha = estim_CAPM(portfolio_ret, data_unique_months)
    CAPM_implied = list(data_unique_months['RF'] + beta *
↪data_unique_months['Mkt-RF'])
    CAPM_implied_percent = [1 + CAPM_implied[i] / 100 for i in
↪range(len(CAPM_implied))]
    CAPM_implied_cumulative = [1 * np.prod(CAPM_implied_percent[0:i+1]) for i in
↪range(len(CAPM_implied_percent))]

    beta_1, beta_2, beta_3, alpha = estim_FF3(portfolio_ret, data_unique_months)
    FF3_implied = list(data_unique_months['RF'] + beta_1 *
↪data_unique_months['Mkt-RF'] + beta_2 * data_unique_months['SMB'] + beta_3 *
↪data_unique_months['HML'])
    FF3_implied_percent = [1 + FF3_implied[i] / 100 for i in
↪range(len(FF3_implied))]
    FF3_implied_cumulative = [1 * np.prod(FF3_implied_percent[0:i+1]) for i in
↪range(len(FF3_implied_percent))]

    beta_1, beta_2, beta_3, beta_4, beta_5, alpha = estim_FF5(portfolio_ret,
↪data_unique_months)
    FF5_implied = list(data_unique_months['RF'] + beta_1 *
↪data_unique_months['Mkt-RF'] + beta_2 * data_unique_months['SMB'] + beta_3 *
↪data_unique_months['HML'] + beta_4 * data_unique_months['RMW'] + beta_5 *
↪data_unique_months['CMA'])
    FF5_implied_percent = [1 + FF5_implied[i] / 100 for i in
↪range(len(FF5_implied))]
    FF5_implied_cumulative = [1 * np.prod(FF5_implied_percent[0:i+1]) for i in
↪range(len(FF5_implied_percent))]

```

```

beta_1, beta_2, beta_3, beta_4, beta_5, beta_6, alpha = 
↪estim_FF5mom(portfolio_ret, data_unique_months)
FF5mom_implied = list(data_unique_months['RF'] + beta_1 * 
↪data_unique_months['Mkt-RF'] + beta_2 * data_unique_months['SMB'] + beta_3 * 
↪data_unique_months['HML'] + beta_4 * data_unique_months['RMW'] + beta_5 * 
↪data_unique_months['CMA'] + beta_6 * data_unique_months['Mom'])
FF5mom_implied_percent = [1 + FF5mom_implied[i] / 100 for i in 
↪range(len(FF5mom_implied))]
FF5mom_implied_cumulative = [1 * np.prod(FF5mom_implied_percent[0:i+1]) for i 
↪in range(len(FF5mom_implied_percent))]

return CAPM_implied_cumulative, FF3_implied_cumulative, 
↪FF5_implied_cumulative, FF5mom_implied_cumulative

```

```

[ ]: def value_signal(group):
    # Calc equal weights
    group['signal'] = group['ME']

    return group

def calc_val_returns(returns):
    ret = [1 + (returns[1][i] - returns[10][i]) for i in range(len(returns[1]))]
    return ret

def calc_returns(returns):
    ret = [1 + (returns[10][i] - returns[1][i]) for i in range(len(returns[1]))]
    return ret

def calc_rolling_ret(group):
    # Calc equal weights
    group['signal'] = group['RET'].rolling(window=11, min_periods = 10).
    ↪apply(lambda x: np.prod(1+x) - 1, raw=True)
    group['signal'] = group['signal'].shift(1)

    return group

def calc_rolling_beta(group):
    # print(list(group['PERMNO'])[0])
    if (len(group) >= 36):
        model = RollingOLS(endog= 100 * group['RET'] - group['RF'], exog= sm.
    ↪add_constant(group['Mkt-RF']), window=36).fit()
        group['signal'] = model.params['Mkt-RF']
    else:
        group['signal'] = np.nan
    return group
    # print(group['signal'][36:])

```

```

[ ]: def sim_portfolio(data, ret_calc, signal_func, equal):
    data = data[(data['date'] >= 196201) & (data['date'] <= 202012)]

    data['ME'] = (data['PRC'] * data['SHROUT'])/1000

    data = data.groupby('PERMNO').apply(signal_func)

    test_data = data.reset_index(drop=True)

    test_data = test_data.dropna(subset = ['signal'])

    test_data = test_data[(test_data['date'] >= 196501) & (test_data['date'] <=
↪202012)]

    test_data['rank'] = test_data.groupby('date')['signal'].rank(pct=True)

    # Label each observation with a decile based on its percentile rank
    test_data['decile'] = np.ceil(test_data['rank']*10)

    test_data = test_data.groupby(['date', 'decile']).apply(calc_weights)

    test_data['decile_lag'] = test_data.groupby('PERMNO')['decile'].shift(1)

    print_mean_ret(test_data.reset_index(drop = True))

    test_data['weights_val_lag'] = test_data.groupby('PERMNO')['weights_val'].
↪shift(1)
    test_data['weights_eq_lag'] = test_data.groupby('PERMNO')['weights_eq'].
↪shift(1)

    test_data['weighted_val_ret'] = test_data['weights_val_lag'] *
↪test_data['RET']
    test_data['weighted_eq_ret'] = test_data['weights_eq_lag'] * test_data['RET']

    test_data = test_data.dropna(subset = ['decile_lag'])

    if equal:
        returns = get_returns(test_data, test_data.reset_index(drop = True).
↪groupby(['decile_lag', 'date']), 'weighted_eq_ret')
    else:
        returns = get_returns(test_data, test_data.reset_index(drop = True).
↪groupby(['decile_lag', 'date']), 'weighted_val_ret')

    portfolio_ret_mom = ret_calc(returns)
    portfolio_val_mom = [1 * np.prod(portfolio_ret_mom[0:i+1]) for i in
↪range(len(portfolio_ret_mom))]

```

```

date_df = test_data.reset_index(drop = True).drop_duplicates(subset='date',
↳keep='first')

capm, ff3, ff5, ff5mom = estim_models(portfolio_ret_mom, portfolio_ret_mom,
↳date_df)

return test_data.reset_index(drop = True), portfolio_ret_mom,
↳portfolio_val_mom, capm, ff3, ff5, ff5mom

```

```

[ ]: def disp_portfolio(data, rets, vals, ff3, capm, ff5, ff5mom):
    mean_ret = np.mean([i - 1 for i in rets])
    var_ret = np.std(rets)
    x_axis = sorted(set(data['date']))
    x_axis = [str(item)[:4] + '-' + str(item)[4:] for item in x_axis]
    print('Sharpe Ratio: {}'.format(mean_ret / var_ret))
    plt.figure(figsize = (20, 8))
    plt.plot(x_axis, vals, label = 'Returns')
    plt.plot(x_axis, ff3, label = 'FF3 Implied Returns')
    plt.plot(x_axis, capm, label = 'CAPM Implied Returns')
    if ff5 is not None:
        plt.plot(x_axis, ff5, label = 'FF5 Implied Returns')
    if ff5mom is not None:
        plt.plot(x_axis, ff5mom, label = 'FF5+Momentum Implied Returns')
    plt.gca().xaxis.set_major_locator(AutoDateLocator())
    plt.legend(loc = 'best')
    plt.show()

```

## 1 Question 2



### Value Weighted Portfolio

The results of our simulated portfolio are below.

2B) As we can see from the output, the mean monthly returns for each decile are not monotonic, but we do see that Decile 1 has the largest returns and Decile 10 has the lowest returns, which was expected.

2C) Mean returns = 0.009 Portfolio volatility = 0.066862 Strategy Sharpe Ratio = 0.129848

2D) The CAPM model regression produces an alpha of 0.7575, while the FF3 model regression produces an alpha of 0.5168. It makes sense that the FF3 model produces lower alpha because the FF3 model includes size and book/market factors. Since our model is taking advantage of a size strategy, it will mostly mirror FF3 returns, making it harder to produce alpha.



2E) Size still works as we can tell from the plotted portfolio values over time. The strategy quickly shrugs off the negative returns generated by the release of the Fama French 1992 paper and the 2002 Dot-Com Bubble burst. However, we do see that after 2002, the strategy's returns are more volatile.



```
[ ]: val_data, val_port_ret, val_port_val, val_capm, val_ff3, val_ff5, val_ff5mom = ␣
      ↪sim_portfolio(ff1926, calc_val_returns, value_signal, False)
      disp_portfolio(val_data, val_port_ret, val_port_val, val_ff3, val_capm, ␣
      ↪val_ff5, None)
```

BY DECILE LAG:

```
Decile 1.0 mean returns: 0.022415183167563028
Decile 2.0 mean returns: 0.010055376201825787
Decile 3.0 mean returns: 0.009539231098490631
Decile 4.0 mean returns: 0.010089036310466308
Decile 5.0 mean returns: 0.009606305406117035
Decile 6.0 mean returns: 0.009809506824385807
Decile 7.0 mean returns: 0.010210128907243644
Decile 8.0 mean returns: 0.009960507740771654
Decile 9.0 mean returns: 0.009862058446141972
Decile 10.0 mean returns: 0.009507285225756973
```

BY DECILE:

```
Decile 1.0 mean returns: -0.01471417431986699
Decile 2.0 mean returns: 0.004632129783649347
Decile 3.0 mean returns: 0.009448779456211311
Decile 4.0 mean returns: 0.011645313693969423
Decile 5.0 mean returns: 0.01400943400402235
Decile 6.0 mean returns: 0.015902528380800647
Decile 7.0 mean returns: 0.01714734991559777
Decile 8.0 mean returns: 0.01824695631800705
Decile 9.0 mean returns: 0.018101130657418057
Decile 10.0 mean returns: 0.016697247639632793
```

Mean returns = 0.009

Portfolio volatility = 0.066862

Strategy Sharpe Ratio = 0.129848

#### OLS Regression Results

```
=====
Dep. Variable:                y      R-squared:                0.018
Model:                        OLS    Adj. R-squared:           0.017
Method:                        Least Squares    F-statistic:           12.54
Date:                          Sat, 20 Apr 2024    Prob (F-statistic):     0.000427
Time:                          01:14:17    Log-Likelihood:        -2220.8
No. Observations:              671    AIC:                   4446.
Df Residuals:                  669    BIC:                   4455.
Df Model:                      1
Covariance Type:               nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.7575	0.258	2.936	0.003	0.251	1.264
Mkt-RF	0.2007	0.057	3.541	0.000	0.089	0.312

```
=====
Omnibus:                      240.708    Durbin-Watson:          1.844
```



Prob(Omnibus):	0.000	Jarque-Bera (JB):	1640.417
Skew:	1.433	Prob(JB):	0.00
Kurtosis:	10.104	Cond. No.	4.59

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.480
Model:	OLS	Adj. R-squared:	0.477
Method:	Least Squares	F-statistic:	205.1
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	3.14e-94
Time:	01:14:17	Log-Likelihood:	-2007.8
No. Observations:	671	AIC:	4024.
Df Residuals:	667	BIC:	4042.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.5168	0.189	2.728	0.007	0.145	0.889
Mkt-RF	-0.0903	0.044	-2.040	0.042	-0.177	-0.003
SMB	1.5425	0.064	24.212	0.000	1.417	1.668
HML	0.0986	0.066	1.489	0.137	-0.031	0.229

Omnibus:	241.324	Durbin-Watson:	2.177
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2585.078
Skew:	1.287	Prob(JB):	0.00
Kurtosis:	12.265	Cond. No.	4.83

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.495
Model:	OLS	Adj. R-squared:	0.492
Method:	Least Squares	F-statistic:	130.6
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	2.78e-96
Time:	01:14:18	Log-Likelihood:	-1997.6
No. Observations:	671	AIC:	4007.
Df Residuals:	665	BIC:	4034.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.6545	0.193	3.399	0.001	0.276	1.033
Mkt-RF	-0.1128	0.046	-2.425	0.016	-0.204	-0.021
SMB	1.4508	0.066	21.902	0.000	1.321	1.581
HML	0.1195	0.088	1.358	0.175	-0.053	0.292
RMW	-0.4104	0.092	-4.449	0.000	-0.592	-0.229
CMA	-0.0153	0.136	-0.113	0.910	-0.283	0.252
=====						
Omnibus:		227.266	Durbin-Watson:		2.194	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		2372.342	
Skew:		1.199	Prob(JB):		0.00	
Kurtosis:		11.894	Cond. No.		5.25	
=====						

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.536
Model:	OLS	Adj. R-squared:	0.532
Method:	Least Squares	F-statistic:	127.8
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	3.36e-107
Time:	01:14:18	Log-Likelihood:	-1969.5
No. Observations:	671	AIC:	3953.
Df Residuals:	664	BIC:	3985.
Df Model:	6		
Covariance Type:	nonrobust		

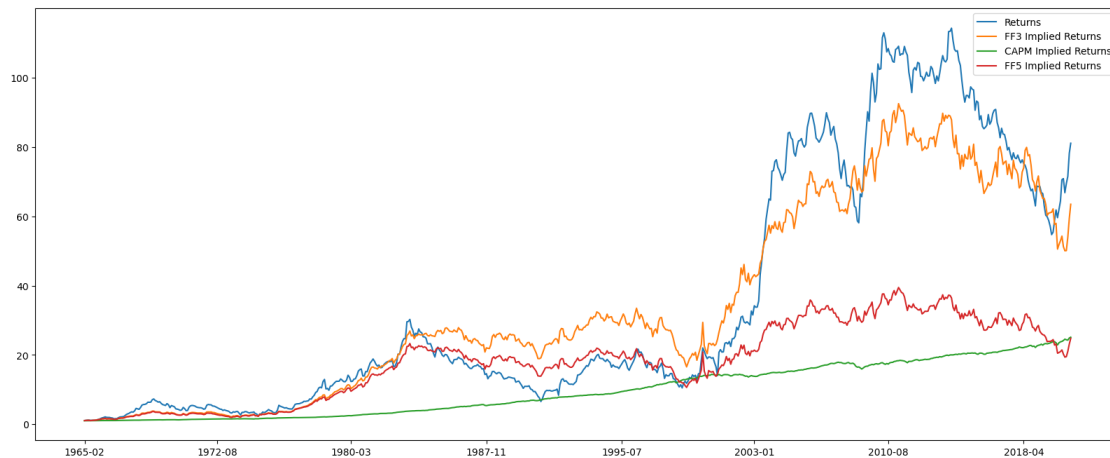
	coef	std err	t	P> t	[0.025	0.975]
const	0.8916	0.187	4.758	0.000	0.524	1.260
Mkt-RF	-0.1654	0.045	-3.663	0.000	-0.254	-0.077
SMB	1.4633	0.064	23.010	0.000	1.338	1.588
HML	-0.0553	0.088	-0.632	0.528	-0.227	0.117
RMW	-0.3406	0.089	-3.827	0.000	-0.515	-0.166
CMA	0.0915	0.131	0.696	0.487	-0.167	0.349
Mom	-0.3337	0.044	-7.613	0.000	-0.420	-0.248
=====						
Omnibus:		162.807	Durbin-Watson:		2.053	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		910.784	
Skew:		0.959	Prob(JB):		1.68e-198	
Kurtosis:		8.375	Cond. No.		5.39	
=====						

Notes:

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

specified.

Sharpe Ratio: 0.12984810010355963



### Equal Weighted Portfolio

The results of our simulated portfolio are below.

2B) As we can see from the output, the mean monthly returns for each decile are not monotonic, but we do see that Decile 1 has the largest returns and Decile 10 has the lowest returns, which was expected.

2C) Mean returns = 0.013 Portfolio volatility = 0.068611 Strategy Sharpe Ratio = 0.188912

2D) The CAPM model regression produces an alpha of 1.2097, while the FF3 model regression produces an alpha of 1.0062. It makes sense that the FF3 model produces lower alpha because the FF3 model includes size and book/market factors. Since our model is taking advantage of a size strategy, it will mostly mirror FF3 returns, making it harder to produce alpha.

2E) Size still works as we can tell from the plotted portfolio values over time. In fact, the equal weighted size portfolio produces substantially more alpha than the FF3 implied returns. This is remarkable given that the FF3 model contains similar factors to size. The strategy quickly shrugs off the negative returns generated by the release of the Fama French 1992 paper and the 2002 Dot-Com Bubble burst. However, we do see that after 2002, the strategy's returns are more volatile.

```
[ ]: val_data, val_port_ret, val_port_val, val_capm, val_ff3, val_ff5, val_ff5mom = \
    ↪sim_portfolio(ff1926, calc_val_returns, value_signal, True)
    disp_portfolio(val_data, val_port_ret, val_port_val, val_ff3, val_capm, \
    ↪val_ff5, None)
```

BY DECILE LAG:

Decile 1.0 mean returns: 0.022415183167563028

Decile 2.0 mean returns: 0.010055376201825787

Decile 3.0 mean returns: 0.009539231098490631

Decile 4.0 mean returns: 0.010089036310466308

Decile 5.0 mean returns: 0.009606305406117035  
 Decile 6.0 mean returns: 0.009809506824385807  
 Decile 7.0 mean returns: 0.010210128907243644  
 Decile 8.0 mean returns: 0.009960507740771654  
 Decile 9.0 mean returns: 0.009862058446141972  
 Decile 10.0 mean returns: 0.009507285225756973

BY DECILE:

Decile 1.0 mean returns: -0.01471417431986699  
 Decile 2.0 mean returns: 0.004632129783649347  
 Decile 3.0 mean returns: 0.009448779456211311  
 Decile 4.0 mean returns: 0.011645313693969423  
 Decile 5.0 mean returns: 0.01400943400402235  
 Decile 6.0 mean returns: 0.015902528380800647  
 Decile 7.0 mean returns: 0.01714734991559777  
 Decile 8.0 mean returns: 0.01824695631800705  
 Decile 9.0 mean returns: 0.018101130657418057  
 Decile 10.0 mean returns: 0.016697247639632793

Mean returns = 0.013

Portfolio volatility = 0.068611

Strategy Sharpe Ratio = 0.188912

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:                0.011
Model:                  OLS    Adj. R-squared:           0.009
Method:                  Least Squares    F-statistic:        7.206
Date:                    Sat, 20 Apr 2024    Prob (F-statistic):    0.00744
Time:                    01:15:51    Log-Likelihood:       -2240.8
No. Observations:        671    AIC:                  4486.
Df Residuals:            669    BIC:                  4495.
Df Model:                 1
Covariance Type:         nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	1.2097	0.266	4.551	0.000	0.688	1.732
Mkt-RF	0.1568	0.058	2.684	0.007	0.042	0.271

```
=====
Omnibus:                280.739    Durbin-Watson:          1.853
Prob(Omnibus):           0.000    Jarque-Bera (JB):       2431.919
Skew:                    1.638    Prob(JB):               0.00
Kurtosis:                11.732    Cond. No.:              4.59
=====
```

Notes:

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

#### OLS Regression Results

```
=====
```

```

Dep. Variable:          y      R-squared:          0.367
Model:                  OLS    Adj. R-squared:       0.364
Method:                 Least Squares  F-statistic:       129.0
Date:                  Sat, 20 Apr 2024  Prob (F-statistic): 6.90e-66
Time:                  01:15:51  Log-Likelihood:    -2090.9
No. Observations:      671     AIC:              4190.
Df Residuals:          667     BIC:              4208.
Df Model:              3
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	1.0062	0.214	4.693	0.000	0.585	1.427
Mkt-RF	-0.1126	0.050	-2.248	0.025	-0.211	-0.014
SMB	1.3947	0.072	19.342	0.000	1.253	1.536
HML	0.0441	0.075	0.588	0.556	-0.103	0.191
Omnibus:	274.356		Durbin-Watson:		2.121	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		3008.117	
Skew:	1.511		Prob(JB):		0.00	
Kurtosis:	12.923		Cond. No.		4.83	

Notes:

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

#### OLS Regression Results

```

Dep. Variable:          y      R-squared:          0.384
Model:                  OLS    Adj. R-squared:       0.379
Method:                 Least Squares  F-statistic:       82.92
Date:                  Sat, 20 Apr 2024  Prob (F-statistic): 1.18e-67
Time:                  01:15:51  Log-Likelihood:    -2081.8
No. Observations:      671     AIC:              4176.
Df Residuals:          665     BIC:              4203.
Df Model:              5
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	1.1480	0.218	5.259	0.000	0.719	1.577
Mkt-RF	-0.1344	0.053	-2.549	0.011	-0.238	-0.031
SMB	1.2975	0.075	17.278	0.000	1.150	1.445
HML	0.0576	0.100	0.577	0.564	-0.138	0.254
RMW	-0.4359	0.105	-4.168	0.000	-0.641	-0.231
CMA	0.0041	0.154	0.027	0.979	-0.299	0.307
Omnibus:	262.013		Durbin-Watson:		2.135	

Prob(Omnibus):	0.000	Jarque-Bera (JB):	2738.252
Skew:	1.440	Prob(JB):	0.00
Kurtosis:	12.468	Cond. No.	5.25

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.423
Model:	OLS	Adj. R-squared:	0.418
Method:	Least Squares	F-statistic:	81.26
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	4.10e-76
Time:	01:15:51	Log-Likelihood:	-2059.6
No. Observations:	671	AIC:	4133.
Df Residuals:	664	BIC:	4165.
Df Model:	6		
Covariance Type:	nonrobust		

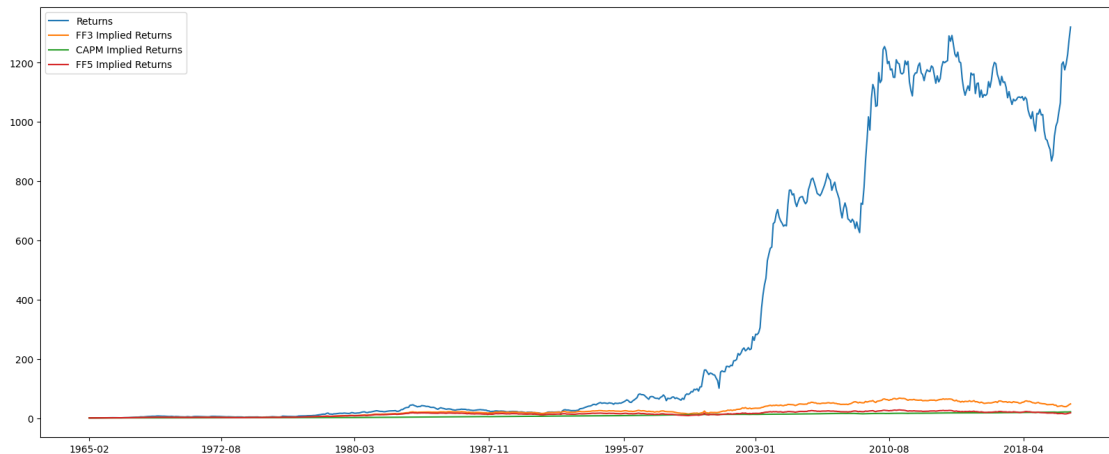
	coef	std err	t	P> t	[0.025	0.975]
const	1.3880	0.214	6.476	0.000	0.967	1.809
Mkt-RF	-0.1876	0.052	-3.633	0.000	-0.289	-0.086
SMB	1.3101	0.073	18.012	0.000	1.167	1.453
HML	-0.1193	0.100	-1.192	0.234	-0.316	0.077
RMW	-0.3653	0.102	-3.588	0.000	-0.565	-0.165
CMA	0.1122	0.150	0.746	0.456	-0.183	0.407
Mom	-0.3376	0.050	-6.734	0.000	-0.436	-0.239

Omnibus:	203.223	Durbin-Watson:	2.007
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1248.668
Skew:	1.205	Prob(JB):	7.16e-272
Kurtosis:	9.233	Cond. No.	5.39

Notes:

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

Sharpe Ratio: 0.18891153624932602



## 2 QUESTION 3

### Value Weighted Portfolio

The results of our simulated portfolio are below.

3B) As we can see from the output, the mean monthly returns for each decile are not monotonic, but we do see that Decile 10 has the largest returns and Decile 1 has the lowest returns, which was expected.

3C) Mean returns = 0.017 Portfolio volatility = 0.082393 Strategy Sharpe Ratio = 0.209300

3D) The CAPM model regression produces an alpha of 1.9810, the FF3 model regression produces an alpha of 2.1777, and the FF5 model produces an alpha of 1.8590. We see that the alphas are significantly positive for all 3 models which makes sense because none of the 3 models price momentum.

3E) The momentum alphas are not indicative of managerial skill. We also ran an FF5+Momentum regression and found that the portfolio returns were essentially mirrored. This indicates that the CAPM, FF3, and FF5 models not pricing the Momentum factor is why the alphas generated are so large in comparison.

```
[ ]: data, port_ret, port_val, capm, ff3, ff5, ff5mom = sim_portfolio(ff1926,
    ↪ calc_returns, calc_rolling_ret, False)
    disp_portfolio(data, port_ret, port_val, ff3, capm, ff5, ff5mom)
```

BY DECILE LAG:

```
Decile 1.0 mean returns: 0.010850477602610726
Decile 2.0 mean returns: 0.007986664296175141
Decile 3.0 mean returns: 0.008929823006912165
Decile 4.0 mean returns: 0.009845679627509233
Decile 5.0 mean returns: 0.009989474979250564
Decile 6.0 mean returns: 0.011053162648848867
Decile 7.0 mean returns: 0.012247417758956958
```

Decile 8.0 mean returns: 0.013588212537821328  
Decile 9.0 mean returns: 0.01493498328610911  
Decile 10.0 mean returns: 0.01718796512784129  
BY DECILE:  
Decile 1.0 mean returns: 0.018314203105449806  
Decile 2.0 mean returns: 0.008315505839602059  
Decile 3.0 mean returns: 0.00797450810219598  
Decile 4.0 mean returns: 0.008828513454974013  
Decile 5.0 mean returns: 0.009424004283223509  
Decile 6.0 mean returns: 0.010501514377887527  
Decile 7.0 mean returns: 0.011251567607604316  
Decile 8.0 mean returns: 0.012029862166717545  
Decile 9.0 mean returns: 0.013280379485287097  
Decile 10.0 mean returns: 0.015650395424091162  
Mean returns = 0.017  
Portfolio volatility = 0.082393  
Strategy Sharpe Ratio = 0.209300

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.068
Model:                        OLS    Adj. R-squared:           0.066
Method:                        Least Squares    F-statistic:            47.78
Date:                          Sat, 20 Apr 2024    Prob (F-statistic):      1.13e-11
Time:                          01:22:13    Log-Likelihood:         -2308.8
No. Observations:              661    AIC:                    4622.
Df Residuals:                  659    BIC:                    4631.
Df Model:                      1
Covariance Type:               nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	1.9810	0.312	6.347	0.000	1.368	2.594
Mkt-RF	-0.4752	0.069	-6.912	0.000	-0.610	-0.340

```

=====
Omnibus:                      140.264    Durbin-Watson:           2.009
Prob(Omnibus):                 0.000    Jarque-Bera (JB):        619.471
Skew:                          -0.894    Prob(JB):                3.04e-135
Kurtosis:                      7.393    Cond. No.                 4.58
=====

```

#### Notes:

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

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.109
Model:                        OLS    Adj. R-squared:           0.105
Method:                        Least Squares    F-statistic:            26.87

```



Date: Sat, 20 Apr 2024 Prob (F-statistic): 2.11e-16  
Time: 01:22:13 Log-Likelihood: -2293.7  
No. Observations: 661 AIC: 4595.  
Df Residuals: 657 BIC: 4613.  
Df Model: 3  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	2.1777	0.308	7.079	0.000	1.574	2.782
Mkt-RF	-0.5224	0.072	-7.227	0.000	-0.664	-0.380
SMB	-0.1520	0.104	-1.467	0.143	-0.355	0.051
HML	-0.5669	0.107	-5.283	0.000	-0.778	-0.356
Omnibus:	144.930		Durbin-Watson:	2.017		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	675.120		
Skew:	-0.909		Prob(JB):	2.51e-147		
Kurtosis:	7.605		Cond. No.	4.83		

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.135			
Model:	OLS	Adj. R-squared:	0.128			
Method:	Least Squares	F-statistic:	20.40			
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	5.99e-19			
Time:	01:22:13	Log-Likelihood:	-2284.1			
No. Observations:	661	AIC:	4580.			
Df Residuals:	655	BIC:	4607.			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	1.8590	0.312	5.950	0.000	1.246	2.472
Mkt-RF	-0.4239	0.076	-5.567	0.000	-0.573	-0.274
SMB	-0.0164	0.108	-0.152	0.879	-0.228	0.195
HML	-0.8669	0.143	-6.055	0.000	-1.148	-0.586
RMW	0.5742	0.150	3.832	0.000	0.280	0.868
CMA	0.6468	0.222	2.919	0.004	0.212	1.082
=====						
Omnibus:	126.086	Durbin-Watson:	2.012			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	564.030			
Skew:	-0.790	Prob(JB):	3.33e-123			
Kurtosis:	7.240	Cond. No.	5.23			

Notes:

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

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.805
Model:                  OLS    Adj. R-squared:      0.804
Method:                 Least Squares  F-statistic:    451.0
Date:                   Sat, 20 Apr 2024  Prob (F-statistic): 1.35e-228
Time:                   01:22:13  Log-Likelihood:  -1791.0
No. Observations:      661      AIC:            3596.
Df Residuals:          654      BIC:            3628.
Df Model:               6
Covariance Type:        nonrobust
=====
```

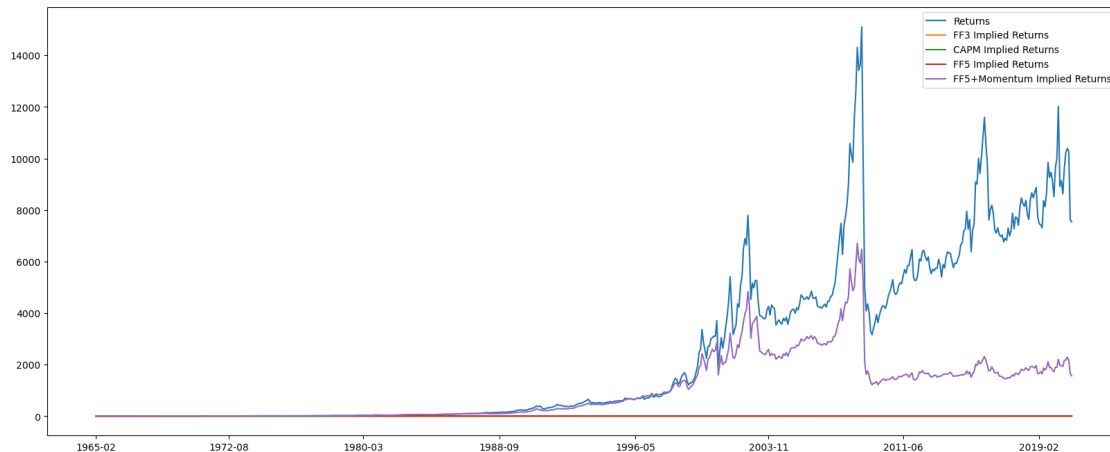
	coef	std err	t	P> t	[0.025	0.975]
const	0.6739	0.150	4.481	0.000	0.379	0.969
Mkt-RF	-0.1489	0.037	-4.067	0.000	-0.221	-0.077
SMB	-0.0936	0.051	-1.826	0.068	-0.194	0.007
HML	0.0161	0.070	0.228	0.820	-0.122	0.154
RMW	0.2259	0.072	3.159	0.002	0.085	0.366
CMA	0.0920	0.106	0.870	0.385	-0.116	0.300
Mom	1.6711	0.035	47.468	0.000	1.602	1.740

```
=====
Omnibus:                 34.563  Durbin-Watson:          2.107
Prob(Omnibus):           0.000  Jarque-Bera (JB):      112.996
Skew:                    0.015  Prob(JB):              2.91e-25
Kurtosis:                 5.025  Cond. No.               5.39
=====
```

Notes:

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

Sharpe Ratio: 0.20930041997819854



## Equal Weighted Portfolio

The results of our simulated portfolio are below.

3B) As we can see from the output, the mean monthly returns for each decile are not monotonic, but we do see that Decile 10 has the largest returns and Decile 1 has the lowest returns, which was expected.

3C) Mean returns = 0.007 Portfolio volatility = 0.071918 Strategy Sharpe Ratio = 0.099123

3D) The CAPM model regression produces an alpha of 0.8444, the FF3 model regression produces an alpha of 1.0103, and the FF5 model produces an alpha of 0.6860. We see that the alphas are significantly positive for all 3 models which makes sense because none of the 3 models price momentum. What's interesting is that the equal weighted portfolio alphas are much lower than the value weighted portfolio alphas. This indicates that weighted portfolios generate higher returns when creating a momentum strategy.

3E) The momentum alphas are not indicative of managerial skill. We also ran an FF5+Momentum regression and found that the FF5+Momentum implied returns dominated equal weighted momentum strategy returns. This indicates that the CAPM, FF3, and FF5 models not pricing the Momentum factor is why the alphas generated are so large in comparison.

```
[ ]: data, port_ret, port_val, capm, ff3, ff5, ff5mom = sim_portfolio(ff1926,
    ↪calc_returns, calc_rolling_ret, True)
disp_portfolio(data, port_ret, port_val, ff3, capm, ff5, ff5mom)
```

BY DECILE LAG:

```
Decile 1.0 mean returns: 0.010850477602610726
Decile 2.0 mean returns: 0.007986664296175141
Decile 3.0 mean returns: 0.008929823006912165
Decile 4.0 mean returns: 0.009845679627509233
Decile 5.0 mean returns: 0.009989474979250564
Decile 6.0 mean returns: 0.011053162648848867
Decile 7.0 mean returns: 0.012247417758956958
Decile 8.0 mean returns: 0.013588212537821328
```

Decile 9.0 mean returns: 0.01493498328610911  
Decile 10.0 mean returns: 0.01718796512784129  
BY DECILE:  
Decile 1.0 mean returns: 0.018314203105449806  
Decile 2.0 mean returns: 0.008315505839602059  
Decile 3.0 mean returns: 0.00797450810219598  
Decile 4.0 mean returns: 0.008828513454974013  
Decile 5.0 mean returns: 0.009424004283223509  
Decile 6.0 mean returns: 0.010501514377887527  
Decile 7.0 mean returns: 0.011251567607604316  
Decile 8.0 mean returns: 0.012029862166717545  
Decile 9.0 mean returns: 0.013280379485287097  
Decile 10.0 mean returns: 0.015650395424091162  
Mean returns = 0.007  
Portfolio volatility = 0.071918  
Strategy Sharpe Ratio = 0.099123

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.023
Model:                  OLS    Adj. R-squared:      0.022
Method:                  Least Squares    F-statistic:      15.74
Date:                    Sat, 20 Apr 2024    Prob (F-statistic):  8.05e-05
Time:                    01:24:01    Log-Likelihood:     -2234.2
No. Observations:        661    AIC:              4472.
Df Residuals:            659    BIC:              4481.
Df Model:                 1
Covariance Type:         nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.8444	0.279	3.028	0.003	0.297	1.392
Mkt-RF	-0.2437	0.061	-3.968	0.000	-0.364	-0.123

```
=====
Omnibus:                435.946    Durbin-Watson:          2.091
Prob(Omnibus):           0.000    Jarque-Bera (JB):       11143.608
Skew:                    -2.515    Prob(JB):               0.00
Kurtosis:                22.476    Cond. No.               4.58
=====
```

#### Notes:

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

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.064
Model:                  OLS    Adj. R-squared:      0.060
Method:                  Least Squares    F-statistic:      15.08
Date:                    Sat, 20 Apr 2024    Prob (F-statistic):  1.68e-09
```

Time: 01:24:02 Log-Likelihood: -2220.0  
 No. Observations: 661 AIC: 4448.  
 Df Residuals: 657 BIC: 4466.  
 Df Model: 3  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	1.0103	0.275	3.671	0.000	0.470	1.551
Mkt-RF	-0.2310	0.065	-3.572	0.000	-0.358	-0.104
SMB	-0.3191	0.093	-3.443	0.001	-0.501	-0.137
HML	-0.3819	0.096	-3.979	0.000	-0.570	-0.193
Omnibus:	432.138		Durbin-Watson:		2.114	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		12528.221	
Skew:	-2.436		Prob(JB):		0.00	
Kurtosis:	23.764		Cond. No.		4.83	

Notes:

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

#### OLS Regression Results

Dep. Variable: y R-squared: 0.099  
 Model: OLS Adj. R-squared: 0.092  
 Method: Least Squares F-statistic: 14.42  
 Date: Sat, 20 Apr 2024 Prob (F-statistic): 2.07e-13  
 Time: 01:24:02 Log-Likelihood: -2207.5  
 No. Observations: 661 AIC: 4427.  
 Df Residuals: 655 BIC: 4454.  
 Df Model: 5  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.6860	0.278	2.465	0.014	0.140	1.232
Mkt-RF	-0.1314	0.068	-1.937	0.053	-0.265	0.002
SMB	-0.1799	0.096	-1.872	0.062	-0.369	0.009
HML	-0.6836	0.128	-5.361	0.000	-0.934	-0.433
RMW	0.5899	0.133	4.420	0.000	0.328	0.852
CMA	0.6493	0.197	3.291	0.001	0.262	1.037
Omnibus:	401.015		Durbin-Watson:		2.110	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		10144.771	
Skew:	-2.225		Prob(JB):		0.00	
Kurtosis:	21.669		Cond. No.		5.23	

Notes:

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

# OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.673
Model:                OLS     Adj. R-squared:       0.670
Method:              Least Squares   F-statistic:      224.2
Date:                Sat, 20 Apr 2024   Prob (F-statistic):  4.90e-155
Time:                01:24:02   Log-Likelihood:    -1872.7
No. Observations:      661     AIC:              3759.
Df Residuals:          654     BIC:              3791.
Df Model:              6
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.2708	0.170	-1.592	0.112	-0.605	0.063
Mkt-RF	0.0906	0.041	2.188	0.029	0.009	0.172
SMB	-0.2422	0.058	-4.178	0.000	-0.356	-0.128
HML	0.0292	0.080	0.367	0.714	-0.127	0.186
RMW	0.3087	0.081	3.815	0.000	0.150	0.468
CMA	0.2014	0.120	1.682	0.093	-0.034	0.437
Mom	1.3492	0.040	33.870	0.000	1.271	1.427

```

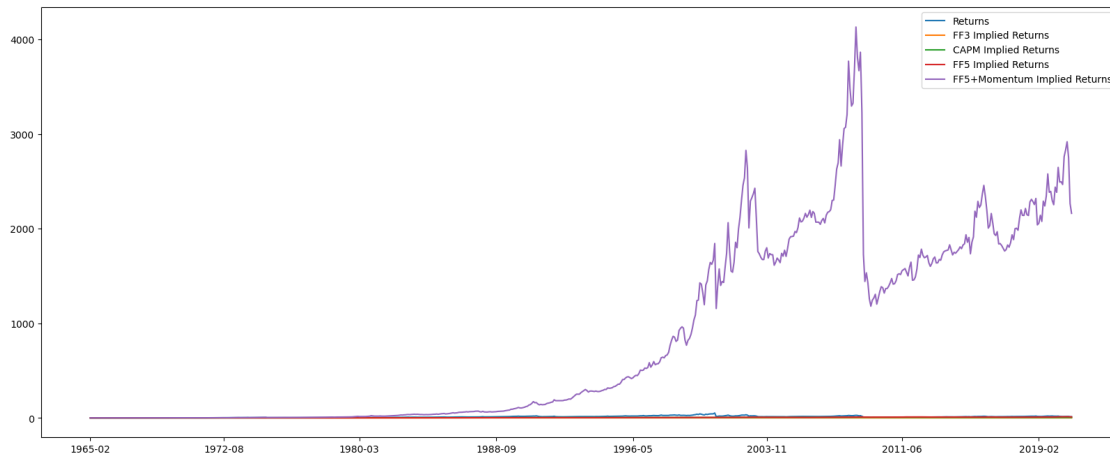
=====
Omnibus:                240.087   Durbin-Watson:          1.992
Prob(Omnibus):           0.000   Jarque-Bera (JB):       2182.229
Skew:                   -1.355   Prob(JB):               0.00
Kurtosis:               11.479   Cond. No.               5.39
=====

```

Notes:

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

Sharpe Ratio: 0.09912280990581032



### 3 QUESTION 4


Value weighted portfolio

4A) The code below displays the average returns (by decile lag is the average return of positions taken) along with the plots of value weighted and equal weighted portfolios of the betting-against-beta strategy.

4B) The mean returns for each decile (as grouped by decile lag since positions are taken based on decile lag) are mostly monotonic except for the 10th decile which decreases a little compared to the 9th decile.

4C) As calculated the mean returns are -.004, volatility of .075, and a sharpe ratio of -.0496. These results are listed below as well.

4D) The plots for the portofflio values of value weighted and equal weighted BAB strategies are plotted below along with the CAPM, FF3, FF5, and FF5 + momentum estimated and implied model returns. The CAPM and FF3 models support a positive alpha as seen in the results below.

4E) To reduce the volatility of this strategy we believe it may be beneficial to choose middle deciles for position-taking rather than end deciles, considering the deciles are split by beta values, the end deciles probably have very high betas in terms of magnitude which also signals higher volatility. Instead, choosing the portfolio with lower beta magnitudes should decrease volatility relative to the market and make the strategy more stable and improve Sharpe ratio. 

```
[ ]: data, port_ret, port_val, capm, ff3, ff5, ff5mom = sim_portfolio(ff1926,
    ↪calc_val_returns, calc_rolling_beta, False)
    disp_portfolio(data, port_ret, port_val, ff3, capm, ff5, ff5mom)
```

BY DECILE LAG:

Decile 1.0 mean returns: 0.010253901674096807

Decile 2.0 mean returns: 0.011652080262312368

Decile 3.0 mean returns: 0.012226792878553312

Decile 4.0 mean returns: 0.012766960332935885

Decile 5.0 mean returns: 0.01275006180459543  
 Decile 6.0 mean returns: 0.013371217389299654  
 Decile 7.0 mean returns: 0.013103725434144703  
 Decile 8.0 mean returns: 0.013798727145176744  
 Decile 9.0 mean returns: 0.01380029890004152  
 Decile 10.0 mean returns: 0.013398765793813074

BY DECILE:

Decile 1.0 mean returns: 0.011674215354769903  
 Decile 2.0 mean returns: 0.010158279977386655  
 Decile 3.0 mean returns: 0.010889974206686455  
 Decile 4.0 mean returns: 0.011009911631782757  
 Decile 5.0 mean returns: 0.011131835253448692  
 Decile 6.0 mean returns: 0.011475427513134108  
 Decile 7.0 mean returns: 0.011872069694315151  
 Decile 8.0 mean returns: 0.012355564417618975  
 Decile 9.0 mean returns: 0.013880027747724188  
 Decile 10.0 mean returns: 0.02274921336071783

Mean returns = -0.004

Portfolio volatility = 0.075971

Strategy Sharpe Ratio = -0.049638

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.504
Model:                  OLS    Adj. R-squared:       0.503
Method:                  Least Squares    F-statistic:      644.0
Date:                    Sat, 20 Apr 2024    Prob (F-statistic): 1.40e-98
Time:                    01:41:36    Log-Likelihood:    -1969.2
No. Observations:        636    AIC:                3942.
Df Residuals:            634    BIC:                3951.
Df Model:                 1
Covariance Type:         nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.2904	0.214	1.356	0.176	-0.130	0.711
Mkt-RF	-1.2191	0.048	-25.376	0.000	-1.313	-1.125

```
=====
Omnibus:                77.160    Durbin-Watson:          1.891
Prob(Omnibus):           0.000    Jarque-Bera (JB):       214.217
Skew:                    -0.605    Prob(JB):               3.04e-47
Kurtosis:                5.573    Cond. No.               4.50
=====
```

Notes:

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

#### OLS Regression Results



```

Dep. Variable:          y      R-squared:          0.598
Model:                  OLS    Adj. R-squared:       0.596
Method:                 Least Squares  F-statistic:       313.7
Date:                   Sat, 20 Apr 2024  Prob (F-statistic): 1.08e-124
Time:                   01:41:36  Log-Likelihood:    -1902.1
No. Observations:      636      AIC:              3812.
Df Residuals:          632      BIC:              3830.
Df Model:               3
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.2373	0.194	1.221	0.222	-0.144	0.619
Mkt-RF	-1.0187	0.046	-21.983	0.000	-1.110	-0.928
SMB	-0.6284	0.065	-9.656	0.000	-0.756	-0.501
HML	0.5286	0.067	7.870	0.000	0.397	0.660
Omnibus:	65.340		Durbin-Watson:	1.916		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	192.502		
Skew:	-0.489		Prob(JB):	1.58e-42		
Kurtosis:	5.511		Cond. No.	4.74		

Notes:

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

#### OLS Regression Results

```

Dep. Variable:          y      R-squared:          0.644
Model:                  OLS    Adj. R-squared:       0.641
Method:                 Least Squares  F-statistic:       228.0
Date:                   Sat, 20 Apr 2024  Prob (F-statistic): 1.06e-138
Time:                   01:41:37  Log-Likelihood:    -1863.6
No. Observations:      636      AIC:              3739.
Df Residuals:          630      BIC:              3766.
Df Model:               5
Covariance Type:       nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1374	0.188	-0.730	0.466	-0.507	0.232
Mkt-RF	-0.9020	0.047	-19.214	0.000	-0.994	-0.810
SMB	-0.4492	0.065	-6.937	0.000	-0.576	-0.322
HML	0.2211	0.086	2.572	0.010	0.052	0.390
RMW	0.7637	0.090	8.523	0.000	0.588	0.940
CMA	0.6330	0.133	4.744	0.000	0.371	0.895
Omnibus:	81.066		Durbin-Watson:	1.947		

Prob(Omnibus):	0.000	Jarque-Bera (JB):	244.354
Skew:	-0.610	Prob(JB):	8.69e-54
Kurtosis:	5.781	Cond. No.	5.15

Notes:

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

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.659
Model:	OLS	Adj. R-squared:	0.656
Method:	Least Squares	F-statistic:	202.6
Date:	Sat, 20 Apr 2024	Prob (F-statistic):	2.39e-143
Time:	01:41:37	Log-Likelihood:	-1850.0
No. Observations:	636	AIC:	3714.
Df Residuals:	629	BIC:	3745.
Df Model:	6		
Covariance Type:	nonrobust		

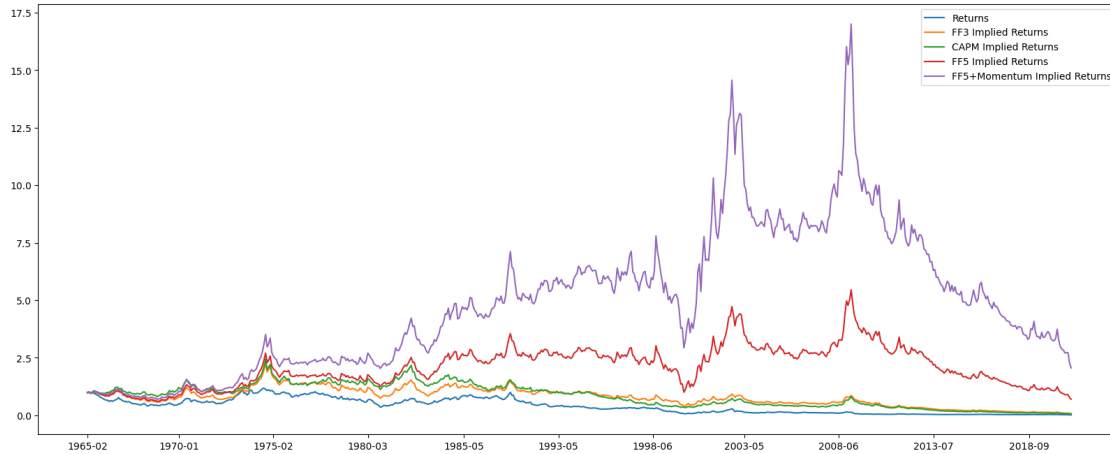
	coef	std err	t	P> t	[0.025	0.975]
const	-0.3125	0.187	-1.667	0.096	-0.681	0.056
Mkt-RF	-0.8581	0.047	-18.361	0.000	-0.950	-0.766
SMB	-0.4593	0.063	-7.239	0.000	-0.584	-0.335
HML	0.3376	0.087	3.876	0.000	0.167	0.509
RMW	0.7193	0.088	8.158	0.000	0.546	0.893
CMA	0.5652	0.131	4.304	0.000	0.307	0.823
Mom	0.2283	0.043	5.254	0.000	0.143	0.314

Omnibus:	34.565	Durbin-Watson:	1.947
Prob(Omnibus):	0.000	Jarque-Bera (JB):	82.980
Skew:	-0.266	Prob(JB):	9.57e-19
Kurtosis:	4.687	Cond. No.	5.38

Notes:

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

Sharpe Ratio: -0.049638046618605644



### Equal Weighted Portfolio

```
[ ]: data, port_ret, port_val, capm, ff3, ff5, ff5mom = sim_portfolio(ff1926,
    ↪calc_val_returns, calc_rolling_beta, True)
disp_portfolio(data, port_ret, port_val, ff3, capm, ff5, ff5mom)
```

BY DECILE LAG:

```
Decile 1.0 mean returns: 0.010253901674096807
Decile 2.0 mean returns: 0.011652080262312368
Decile 3.0 mean returns: 0.012226792878553312
Decile 4.0 mean returns: 0.012766960332935885
Decile 5.0 mean returns: 0.01275006180459543
Decile 6.0 mean returns: 0.013371217389299654
Decile 7.0 mean returns: 0.013103725434144703
Decile 8.0 mean returns: 0.013798727145176744
Decile 9.0 mean returns: 0.01380029890004152
Decile 10.0 mean returns: 0.013398765793813074
```

BY DECILE:

```
Decile 1.0 mean returns: 0.011674215354769903
Decile 2.0 mean returns: 0.010158279977386655
Decile 3.0 mean returns: 0.010889974206686455
Decile 4.0 mean returns: 0.011009911631782757
Decile 5.0 mean returns: 0.011131835253448692
Decile 6.0 mean returns: 0.011475427513134108
Decile 7.0 mean returns: 0.011872069694315151
Decile 8.0 mean returns: 0.012355564417618975
Decile 9.0 mean returns: 0.013880027747724188
Decile 10.0 mean returns: 0.02274921336071783
```

Mean returns = -0.003

Portfolio volatility = 0.070571

Strategy Sharpe Ratio = -0.038104

OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.539
Model:                        OLS    Adj. R-squared:           0.538
Method:                      Least Squares  F-statistic:             739.8
Date:                        Sat, 20 Apr 2024  Prob (F-statistic):      1.49e-108
Time:                        02:02:06  Log-Likelihood:          -1899.3
No. Observations:            636      AIC:                    3803.
Df Residuals:                634      BIC:                    3812.
Df Model:                    1
Covariance Type:             nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.3721        0.192        1.940      0.053      -0.005        0.749
Mkt-RF        -1.1707        0.043     -27.200      0.000      -1.255      -1.086
=====

```

```

=====
Omnibus:                331.074  Durbin-Watson:           1.915
Prob(Omnibus):           0.000  Jarque-Bera (JB):         5195.923
Skew:                    -1.931  Prob(JB):                 0.00
Kurtosis:                16.459  Cond. No.                 4.50
=====

```

Notes:

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

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.627
Model:                        OLS    Adj. R-squared:           0.625
Method:                      Least Squares  F-statistic:             354.4
Date:                        Sat, 20 Apr 2024  Prob (F-statistic):      6.12e-135
Time:                        02:02:06  Log-Likelihood:          -1831.4
No. Observations:            636      AIC:                    3671.
Df Residuals:                632      BIC:                    3689.
Df Model:                    3
Covariance Type:             nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.4190        0.174        2.410      0.016        0.078        0.760
Mkt-RF        -0.9973        0.041     -24.050      0.000      -1.079      -0.916
SMB           -0.6889        0.058     -11.830      0.000      -0.803      -0.575
HML           0.2266        0.060        3.770      0.000        0.109        0.345
=====

```

```

=====
Omnibus:                343.907  Durbin-Watson:           1.857
Prob(Omnibus):           0.000  Jarque-Bera (JB):         6205.329
Skew:                    -1.986  Prob(JB):                 0.00
Kurtosis:                17.778  Cond. No.                 4.74
=====

```

Notes:

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

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.665
Model:                  OLS    Adj. R-squared:      0.662
Method:                 Least Squares  F-statistic:      249.8
Date:                  Sat, 20 Apr 2024  Prob (F-statistic):  7.42e-147
Time:                  02:02:06  Log-Likelihood:    -1797.7
No. Observations:      636     AIC:              3607.
Df Residuals:          630     BIC:              3634.
Df Model:               5
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.1575	0.170	0.928	0.354	-0.176	0.491
Mkt-RF	-0.9341	0.042	-22.072	0.000	-1.017	-0.851
SMB	-0.5327	0.058	-9.125	0.000	-0.647	-0.418
HML	0.1053	0.078	1.359	0.175	-0.047	0.258
RMW	0.6780	0.081	8.392	0.000	0.519	0.837
CMA	0.2073	0.120	1.723	0.085	-0.029	0.444

```

=====
Omnibus:                 351.761  Durbin-Watson:          1.876
Prob(Omnibus):           0.000   Jarque-Bera (JB):        5833.606
Skew:                    -2.081   Prob(JB):                 0.00
Kurtosis:                17.241   Cond. No.                 5.15
=====

```

Notes:

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

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.722
Model:                  OLS    Adj. R-squared:      0.719
Method:                 Least Squares  F-statistic:      272.3
Date:                  Sat, 20 Apr 2024  Prob (F-statistic):  3.73e-171
Time:                  02:02:06  Log-Likelihood:    -1738.1
No. Observations:      636     AIC:              3490.
Df Residuals:          629     BIC:              3521.
Df Model:               6
Covariance Type:       nonrobust
=====

```

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

const	-0.1607	0.157	-1.022	0.307	-0.469	0.148
Mkt-RF	-0.8544	0.039	-21.795	0.000	-0.931	-0.777
SMB	-0.5511	0.053	-10.355	0.000	-0.656	-0.447
HML	0.3170	0.073	4.339	0.000	0.174	0.461
RMW	0.5974	0.074	8.077	0.000	0.452	0.743
CMA	0.0842	0.110	0.765	0.445	-0.132	0.301
Mom	0.4150	0.036	11.385	0.000	0.343	0.487
=====						
Omnibus:		181.740	Durbin-Watson:		1.792	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		1254.778	
Skew:		-1.083	Prob(JB):		3.38e-273	
Kurtosis:		9.531	Cond. No.		5.38	
=====						

Notes:

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

Sharpe Ratio: -0.03810392908449324

