

# BEM114\_HW2\_Andrew\_Daniel\_Kyle

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## 1 BEM114 Homework 2 - Statistical Arbitrage

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### 1.1 Setup

Imports, Helper Functions, and DataFrames

```
[1]: '''  
Imports  
'''  
  
import pandas as pd  
import numpy as np  
from statsmodels.regression.rolling import RollingOLS  
import statsmodels.api as sm  
  
import matplotlib.pyplot as plt
```

```
[2]: '''  
Helper functions  
'''  
  
# Given a group of stocks, calculate equal-weighted and value-weighted weights  
def calc_weights(group):  
    # Calc equal weights  
    group['weights_eq'] = 1 / float(group['decile'].count())  
    # Calc total market equity of group  
    group['TMV'] = group['MV'].sum()  
    # Calc value weights  
    group['weights_val'] = group['MV'] / group['TMV']  
    return group  
  
# Part b of problems 2,3,4: Calculates monthly returns from monthly weights  
def part_b(df):  
    # Calculate weights times returns  
    df['weighted_val_ret'] = df['weights_val_lag'] * df['RET']
```

```

df['weighted_eq_ret'] = df['weights_eq_lag'] * df['RET']

# Sum up portfolio returns
eqports = df.groupby(['date', 'decile_lag'])['weighted_eq_ret'].sum()
eqports = eqports.unstack()

# Drop if missing accounting data in early years
eqports = eqports.dropna(axis=0)

# Match data format of FF factors
eqports = eqports * 100
eqports = eqports.reset_index()

valports = df.groupby(['date', 'decile_lag'])['weighted_val_ret'].sum()
valports = valports.unstack()
valports = valports.dropna(axis=0)
valports = valports * 100
valports = valports.reset_index()

return eqports, valports

# Creates a graph of the decile mean returns
def graph_deciles(df, title):
    df_mean = df.mean(numeric_only=True)
    df_mean.plot(kind='bar', x='Decile Portfolio', y='values', legend=False)
    plt.xlabel('Decile Portfolio')
    plt.ylabel('Mean Monthly Returns')
    plt.title(title)
    plt.show()

# Calculates returns and prints the returns mean, vol, and Sharpe ratio for a
↳ strategy
def analyze(df, strat_name, ret_col_name, reverse=False):
    df[ret_col_name] = df[10.0] - df[1.0] if reverse else df[1.0] - df[10.0]

    strat_mean = df[ret_col_name].mean()
    strat_vol = df[ret_col_name].std()
    strat_sharpe = strat_mean / strat_vol

    print(f"{strat_name} monthly returns have mean {strat_mean}%, vol_
    ↳ {strat_vol}%, and Sharpe {strat_sharpe}")

# Estimates the CAPM and FF3 models on df_old using the returns found in
↳ ret_col_name
def estimate_capm_and_ff3(df_old, ret_col_name, ff3):
    # Merge in ff3 data. Keep separate from ff5 because there is a larger data_
    ↳ range available in ff3.

```

```

    # May lose a few rows since ff3 goes back to July 1926 and our data starts
    ↪ Jan 1926
    df = pd.merge(df_old, ff3, how='inner', on=['date'])

    # Estimate CAPM
    print('CAPM')
    print(sm.OLS(df[ret_col_name] - df['RF'], sm.add_constant(df[['Mkt-RF']])))
    ↪ fit().summary()

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

# Estimates the FF5 model on df_old using the returns found in ret_col_name,
    ↪ optionally adding momentum
def estimate_ff5(df_old, ret_col_name, ff5, add_momentum=False, mom_rets=None):
    # Merge in ff5 data. Truncates dates so create a df separate from ff3.
    df = pd.merge(df_old, ff5, how='inner', on=['date'])

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

    if add_momentum:
        # Estimate FF5 + Momentum
        print('FF5 + Momentum')
        df = pd.merge(df, mom_rets, how='inner', on=['date'])
        print(sm.OLS(df[ret_col_name] - df['RF'], sm.add_constant(df[['Mkt-RF'],
    ↪ 'SMB', 'HML', 'RMW', 'CMA', 'MOM']]))).fit().summary())

```

```

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

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

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

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

# Drop day information in the dates

```

```
df['date'] = df['date'].str[:3]
```

```
[4]: '''
      Load FF3 and FF5 data
      '''

ff3 = pd.read_csv('ff3_factors.csv')
ff3 = ff3.astype({'date': 'string'})
ff3['date'] = ff3['date'].apply(lambda x: x[:4] + '-' + x[4:])

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

## 1.2 Problem 1

### 1.2.1 Part A

```
[5]: # Filter SHRCDD and EXCHCD, set negative prices to NA
df = df[df['SHRCDD'].isin([10, 11])]
df = df[df['EXCHCD'].isin([1, 2, 3])]
df.loc[df['PRC'] < 0, 'PRC'] = 'NA'
df
```

```
[5]:
```

	PERMNO	date	SHRCDD	EXCHCD	PRC	RET	SHROUT
2	10000	1986-02	10	3	NA	-0.257143	3680.0
3	10000	1986-03	10	3	NA	0.365385	3680.0
4	10000	1986-04	10	3	NA	-0.098592	3793.0
5	10000	1986-05	10	3	NA	-0.222656	3793.0
6	10000	1986-06	10	3	NA	-0.005025	3793.0
...	...	...	...	...	...	...	...
4705164	93436	2020-08	11	3	498.32001	0.741452	931809.0
4705165	93436	2020-09	11	3	429.01001	-0.139087	948000.0
4705166	93436	2020-10	11	3	388.04001	-0.095499	947901.0
4705167	93436	2020-11	11	3	567.59998	0.462736	947901.0
4705168	93436	2020-12	11	3	705.66998	0.243252	959854.0

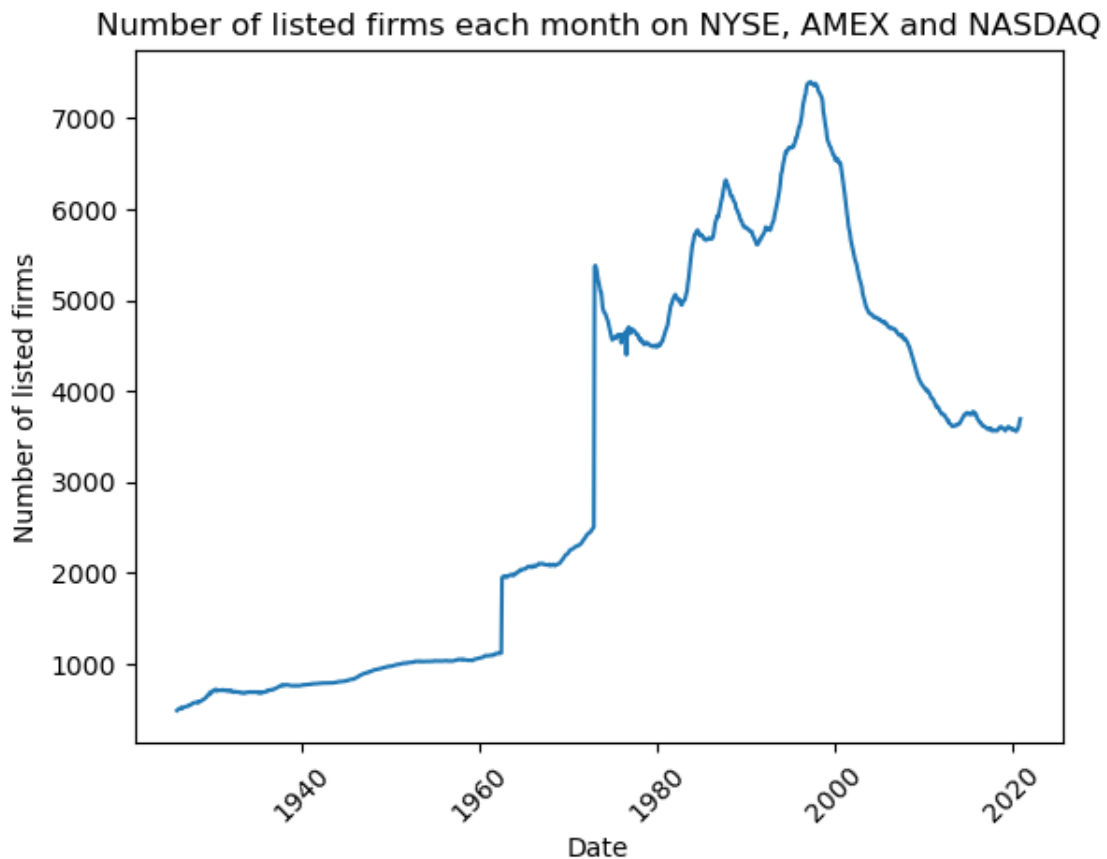
[3563041 rows x 7 columns]

### 1.2.2 Part B

```
[6]: # Group by year and month
by_month = df.groupby(df['date'])['PERMNO'].nunique().reset_index()
by_month['date'] = pd.to_datetime(by_month['date'])

# Create plot of number of firms listed each month
plt.plot(by_month['date'], by_month['PERMNO'])
```

```
plt.title('Number of listed firms each month on NYSE, AMEX and NASDAQ')
plt.xlabel('Date')
plt.ylabel('Number of listed firms')
plt.xticks(rotation=45)
plt.show()
```



## 1.3 Problem 2

### 1.3.1 Part A

```
[7]: # Drop NA prices and create MV column
df['PRC'] = pd.to_numeric(df['PRC'], errors='coerce')
df = df.dropna(subset=['PRC'])
df['MV'] = df['PRC'] * df['SHROUT']

sortdf = df.copy()
sortdf['rank'] = sortdf.groupby('date')['MV'].rank(pct=True)

# Label decile portfolios
sortdf['decile'] = np.ceil(sortdf['rank']*10)
```

```

# Calculate weights
# Introduces Nans because some rows do not have BM_decile
sortdf = sortdf.groupby(['date', 'decile'], group_keys=False).
    ↪ apply(calc_weights)

# Move weights and deciles forward one month
# We form portfolios at the end of this month, and then earn returns over
# the next month.
sortdf['decile_lag'] = sortdf.groupby('PERMNO')['decile'].shift(1)
sortdf['weights_val_lag'] = sortdf.groupby('PERMNO')['weights_val'].shift(1)
sortdf['weights_eq_lag'] = sortdf.groupby('PERMNO')['weights_eq'].shift(1)

sortdf = sortdf.drop(['rank', 'decile', 'weights_eq', 'TMV', 'weights_val'],
    ↪ axis=1)
sortdf

```

/var/folders/24/b7637qzn5pz9\_133fc30f4240000gn/T/ipykernel\_92939/2236265313.py:4

: 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)

```
df['MV'] = df['PRC'] * df['SHROUT']
```

```

[7]:
      PERMNO  date  SHRC D  EXCHCD  PRC  RET  SHROUT  \
28      10001  1986-09    11     3   6.37500 -0.003077   991.0
29      10001  1986-10    11     3   6.62500  0.039216   991.0
30      10001  1986-11    11     3   7.00000  0.056604   991.0
31      10001  1986-12    11     3   7.00000  0.015000   991.0
32      10001  1987-01    11     3   6.75000 -0.035714   991.0
...
4705164  93436  2020-08    11     3  498.32001  0.741452  931809.0
4705165  93436  2020-09    11     3  429.01001 -0.139087  948000.0
4705166  93436  2020-10    11     3  388.04001 -0.095499  947901.0
4705167  93436  2020-11    11     3  567.59998  0.462736  947901.0
4705168  93436  2020-12    11     3  705.66998  0.243252  959854.0

      MV  decile_lag  weights_val_lag  weights_eq_lag
28      6.317625e+03      NaN      NaN      NaN
29      6.565375e+03      1.0      0.001939      0.002494
30      6.937000e+03      1.0      0.001996      0.002469
31      6.937000e+03      1.0      0.002139      0.002551
32      6.689250e+03      1.0      0.002337      0.002309
...
4705164  4.643391e+08     10.0      0.009859      0.002825

```

4705165	4.067015e+08	10.0	0.015874	0.002809
4705166	3.678235e+08	10.0	0.014459	0.002801
4705167	5.380286e+08	10.0	0.013439	0.002793
4705168	6.773402e+08	10.0	0.017566	0.002740

[2855895 rows x 11 columns]

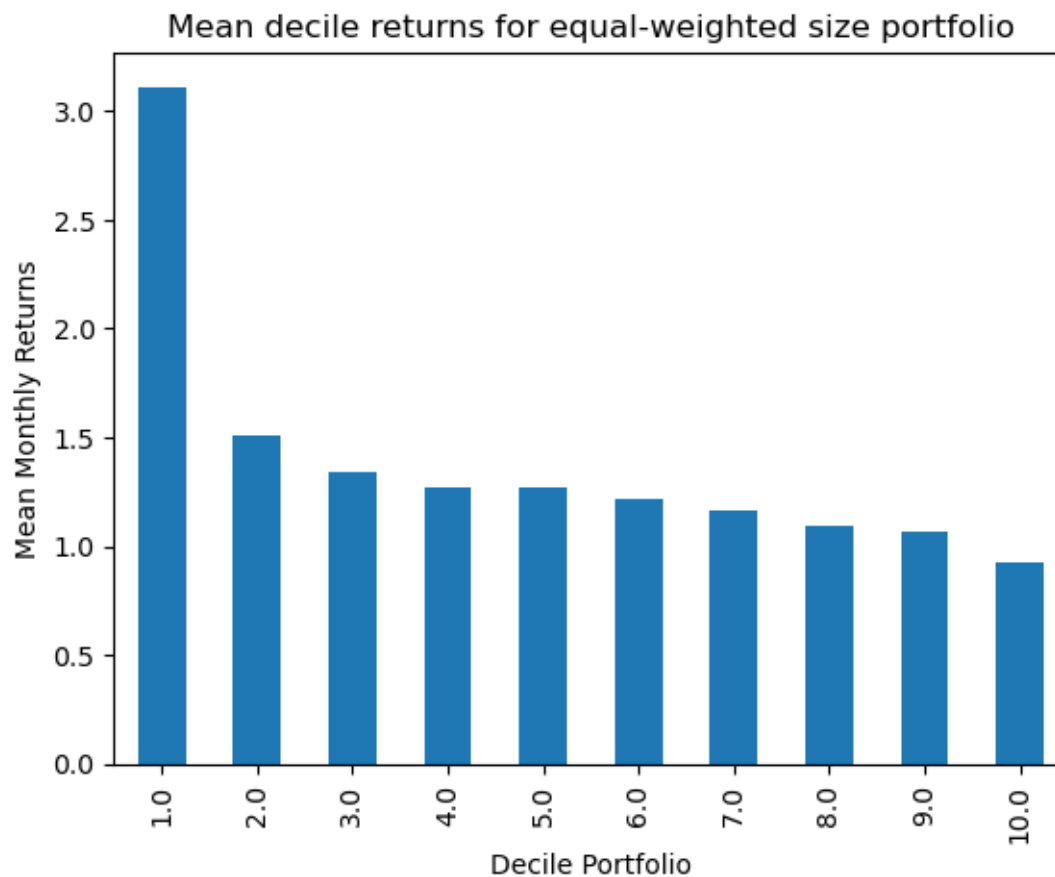
### 1.3.2 Part B

```
[8]: eqports, valports = part_b(sortdf)

display(eqports.mean(numeric_only=True))
graph_deciles(eqports, 'Mean decile returns for equal-weighted size portfolio')

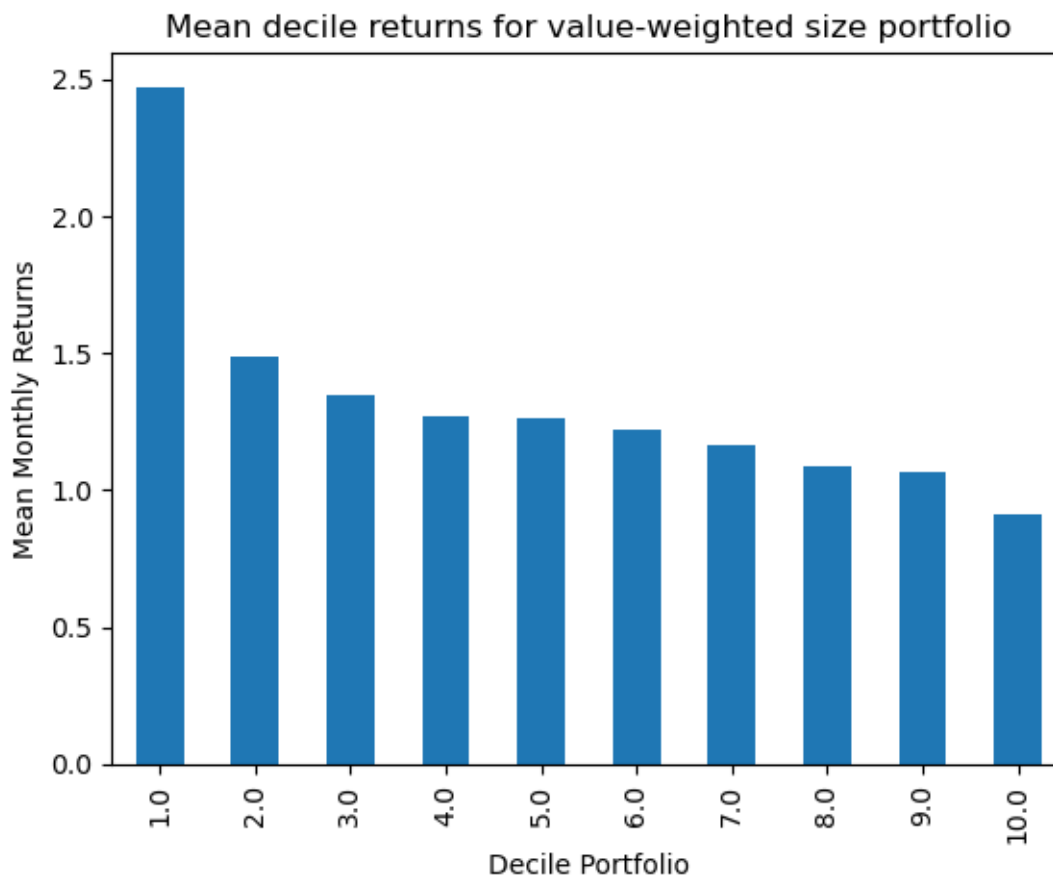
display(valports.mean(numeric_only=True))
graph_deciles(valports, 'Mean decile returns for value-weighted size portfolio')
```

```
decile_lag
1.0      3.110296
2.0      1.509020
3.0      1.337370
4.0      1.272587
5.0      1.267089
6.0      1.215686
7.0      1.162114
8.0      1.092401
9.0      1.070809
10.0     0.924893
dtype: float64
```



```
decile_lag
1.0      2.471250
2.0      1.486205
3.0      1.343516
4.0      1.268714
5.0      1.264068
6.0      1.217934
7.0      1.160938
8.0      1.084152
9.0      1.064744
10.0     0.912878
dtype: float64
```





The mean monthly returns appear to be monotonic in both the equal-weighted and value-weighted portfolios. The mean returns decrease as size increases.

### 1.3.3 Part C

```
[9]: analyze(eqports, 'Equal-weighted Size', 'RET')
      analyze(valports, 'Value-weighted Size', 'RET')
```

Equal-weighted Size monthly returns have mean 2.1854033471142524%, vol 15.054678304411805%, and Sharpe 0.14516440025648475  
 Value-weighted Size monthly returns have mean 1.5583727812713861%, vol 12.915460300728482%, and Sharpe 0.12065948444620962

### 1.3.4 Part D

```
[10]: print('Equal-Weighted Size:')
      print('-----')
      estimate_capm_and_ff3(eqports, 'RET', ff3)

      print('\n\n\n\nValue-Weighted Size:')
```

```
print('-----')
estimate_capm_and_ff3(valports, 'RET', ff3)
```

Equal-Weighted Size:

--

CAPM

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.170
Model:                  OLS    Adj. R-squared:      0.169
Method:                 Least Squares    F-statistic:      231.7
Date:                   Mon, 22 Apr 2024    Prob (F-statistic): 9.47e-48
Time:                   00:13:34    Log-Likelihood:    -4581.7
No. Observations:      1134    AIC:              9167.
Df Residuals:          1132    BIC:              9177.
Df Model:               1
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	1.1508	0.412	2.793	0.005	0.342	1.959
Mkt-RF	1.1627	0.076	15.223	0.000	1.013	1.313

```
=====
Omnibus:                1632.470    Durbin-Watson:          1.706
Prob(Omnibus):           0.000    Jarque-Bera (JB):       597390.160
Skew:                    8.042    Prob(JB):               0.00
Kurtosis:                114.286    Cond. No.               5.44
=====
```

Notes:

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

FF3

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.584
Model:                  OLS    Adj. R-squared:      0.583
Method:                 Least Squares    F-statistic:      529.6
Date:                   Mon, 22 Apr 2024    Prob (F-statistic): 7.41e-215
Time:                   00:13:34    Log-Likelihood:    -4189.4
No. Observations:      1134    AIC:              8387.
Df Residuals:          1130    BIC:              8407.
Df Model:               3
Covariance Type:       nonrobust
=====
```

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

const	0.6092	0.292	2.083	0.037	0.035	1.183
Mkt-RF	0.4166	0.058	7.122	0.000	0.302	0.531
SMB	2.5175	0.096	26.121	0.000	2.328	2.707
HML	1.6717	0.085	19.674	0.000	1.505	1.838
=====						
Omnibus:		1208.710	Durbin-Watson:			1.825
Prob(Omnibus):		0.000	Jarque-Bera (JB):			152550.865
Skew:		4.857	Prob(JB):			0.00
Kurtosis:		58.984	Cond. No.			5.71
=====						

Notes:

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

Value-Weighted Size:

--

CAPM

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:                0.195
Model:                  OLS    Adj. R-squared:            0.194
Method:                 Least Squares    F-statistic:        274.4
Date:                  Mon, 22 Apr 2024    Prob (F-statistic):    2.34e-55
Time:                  00:13:34    Log-Likelihood:       -4390.6
No. Observations:      1134    AIC:                  8785.
Df Residuals:          1132    BIC:                  8795.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.5797	0.348	1.665	0.096	-0.103	1.263
Mkt-RF	1.0692	0.065	16.566	0.000	0.943	1.196

```

=====
Omnibus:                1453.246    Durbin-Watson:        1.709
Prob(Omnibus):          0.000    Jarque-Bera (JB):     327541.754
Skew:                   6.574    Prob(JB):              0.00
Kurtosis:               85.215    Cond. No.              5.44
=====

```

Notes:

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

specified.  
FF3

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.646
Model:	OLS	Adj. R-squared:	0.645
Method:	Least Squares	F-statistic:	686.2
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	6.08e-254
Time:	00:13:34	Log-Likelihood:	-3925.5
No. Observations:	1134	AIC:	7859.
Df Residuals:	1130	BIC:	7879.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.1060	0.232	0.457	0.648	-0.349	0.561
Mkt-RF	0.4015	0.046	8.664	0.000	0.311	0.492
SMB	2.3121	0.076	30.275	0.000	2.162	2.462
HML	1.4252	0.067	21.169	0.000	1.293	1.557

Omnibus:	1005.072	Durbin-Watson:	1.876
Prob(Omnibus):	0.000	Jarque-Bera (JB):	65012.508
Skew:	3.748	Prob(JB):	0.00
Kurtosis:	39.328	Cond. No.	5.71

#### Notes:

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

For both the equal-weighted and value-weighted portfolios, the alphas for the CAPM model are greater than that of the FF3 model. In the equal-weighted portfolio, the alpha for the CAPM model is 1.15 while the alpha for the FF3 model is 0.61. In the value-weighted portfolio, the alpha for the CAPM model is 0.58 while the alpha for the FF3 model is 0.11.

This makes sense with our strategy formulation because the equal-weight portfolio, if we are able to execute it, would put higher weight on the stocks we believe are undervalued (low size), causing higher alpha. From these numbers, we can also see that the alphas calculated from CAPM are higher than those from FF3.

#### 1.3.5 Part E

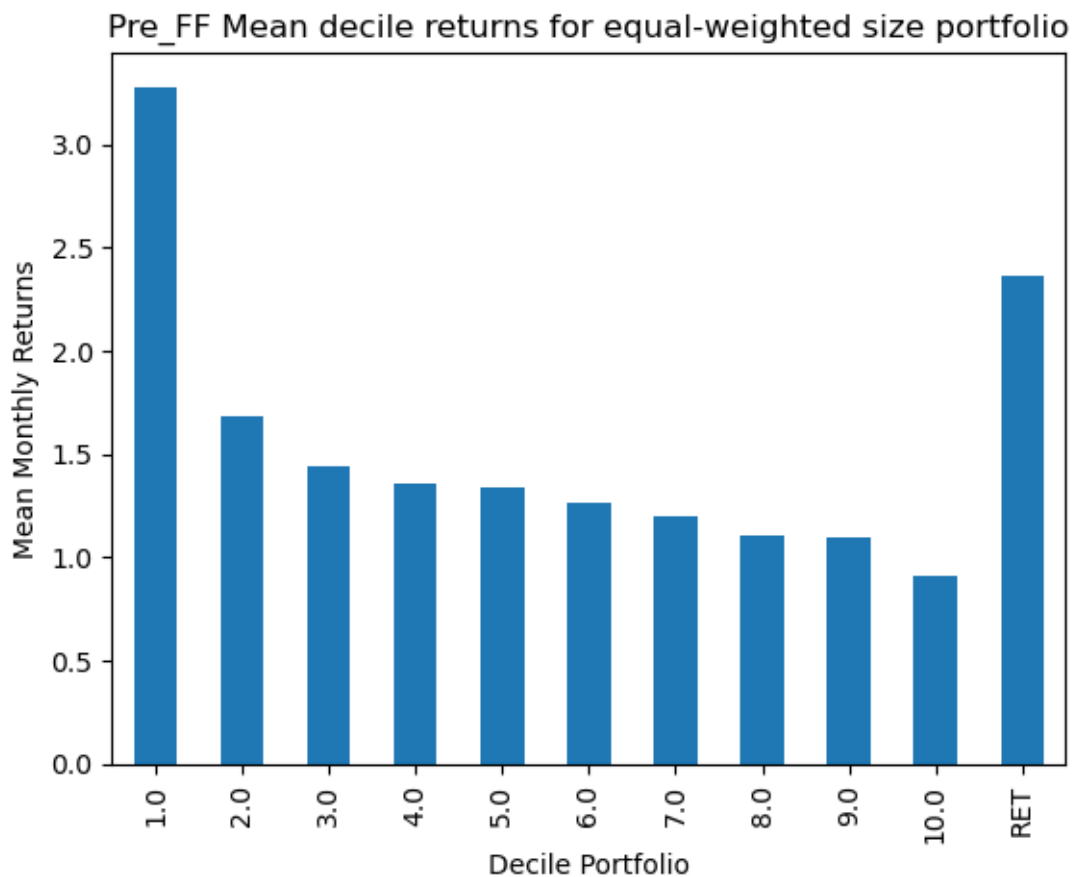
```
[11]: pre_FF = eqports[eqports['date'] < '1992-00'].copy()

analyze(pre_FF, 'Equal-weighted Size', 'RET')
display(pre_FF.mean(numeric_only=True))
```

```
graph_deciles(pre_FF, 'Pre_FF Mean decile returns for equal-weighted size_
↳portfolio')
estimate_capm_and_ff3(pre_FF, 'RET', ff3)
```

Equal-weighted Size monthly returns have mean 2.366380613074474%, vol  
17.34598770401589%, and Sharpe 0.13642236195789625

```
decile_lag
1.0      3.278559
2.0      1.684028
3.0      1.444906
4.0      1.361792
5.0      1.335321
6.0      1.266390
7.0      1.202053
8.0      1.107576
9.0      1.092938
10.0     0.912178
RET      2.366381
dtype: float64
```



## CAPM

## OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.216
Model:                  OLS    Adj. R-squared:       0.215
Method:                 Least Squares  F-statistic:      216.2
Date:                  Mon, 22 Apr 2024  Prob (F-statistic): 2.09e-43
Time:                  00:13:34  Log-Likelihood:   -3265.2
No. Observations:      786     AIC:              6534.
Df Residuals:          784     BIC:              6544.
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          1.1710      0.554        2.113      0.035      0.083      2.259
Mkt-RF          1.4090      0.096       14.704      0.000      1.221      1.597
=====

```

```

=====
Omnibus:          1085.296   Durbin-Watson:          1.705
Prob(Omnibus):    0.000     Jarque-Bera (JB):       263830.027
Skew:             7.333     Prob(JB):                0.00
Kurtosis:         91.548    Cond. No.                5.82
=====

```

## Notes:

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

## FF3

## OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.698
Model:                  OLS    Adj. R-squared:       0.697
Method:                 Least Squares  F-statistic:      602.6
Date:                  Mon, 22 Apr 2024  Prob (F-statistic): 8.38e-203
Time:                  00:13:34  Log-Likelihood:   -2890.3
No. Observations:      786     AIC:              5789.
Df Residuals:          782     BIC:              5807.
Df Model:               3
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.3366      0.345        0.974      0.330     -0.342      1.015
Mkt-RF          0.4024      0.066        6.091      0.000      0.273      0.532
SMB             3.0060      0.117       25.685      0.000      2.776      3.236
HML             1.9846      0.100       19.784      0.000      1.788      2.182
=====

```

```
=====
Omnibus:                782.943    Durbin-Watson:                1.772
Prob(Omnibus):          0.000    Jarque-Bera (JB):          68582.445
Skew:                   4.312    Prob(JB):                  0.00
Kurtosis:               47.942    Cond. No.                  6.21
=====
```

Notes:

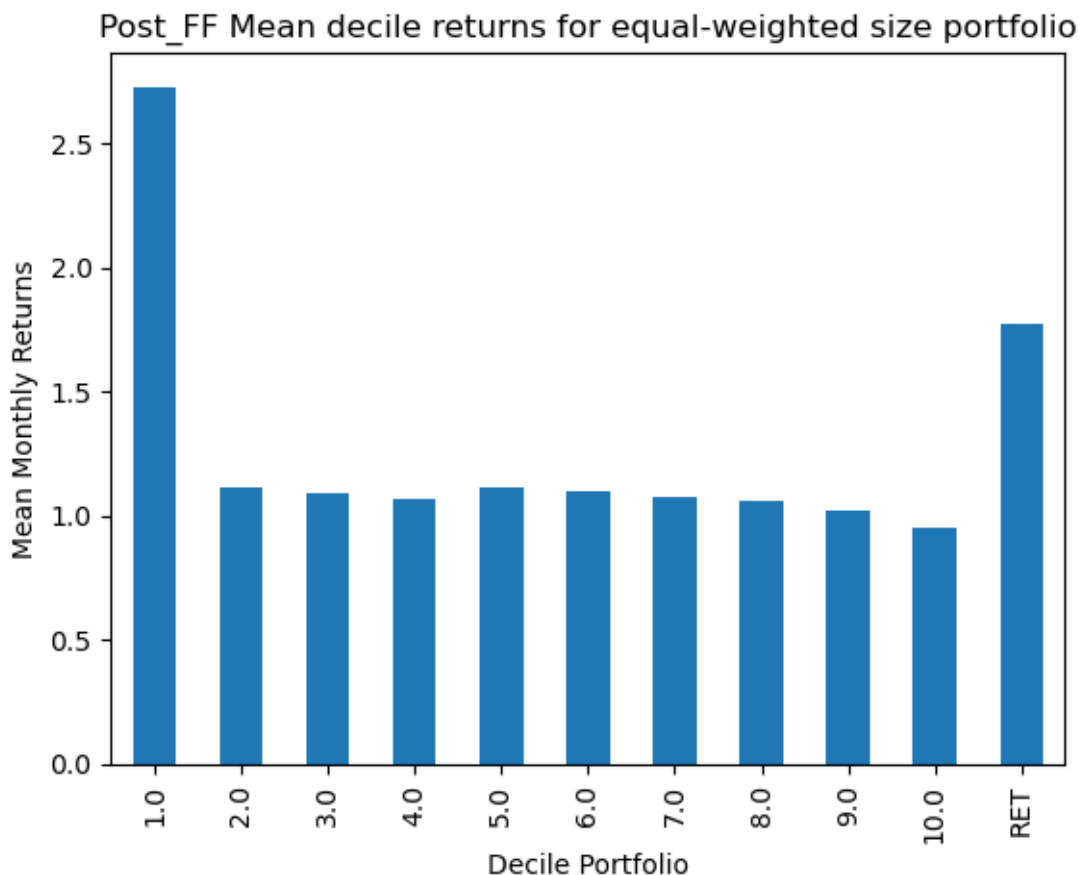
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[12]: post_FF = eqports[eqports['date'] > '1992-00'].copy()

analyze(post_FF, 'Equal-weighted Size', 'RET')
display(post_FF.mean(numeric_only=True))
graph_deciles(post_FF, 'Post_FF Mean decile returns for equal-weighted size_
↳portfolio')
estimate_capm_and_ff3(post_FF, 'RET', ff3)
```

Equal-weighted Size monthly returns have mean 1.7740441017851276%, vol 7.61795357856323%, and Sharpe 0.23287672778385687

```
decile_lag
1.0      2.727837
2.0      1.111228
3.0      1.092943
4.0      1.069827
5.0      1.112000
6.0      1.100437
7.0      1.071333
8.0      1.057907
9.0      1.020510
10.0     0.953793
RET      1.774044
dtype: float64
```



CAPM

#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.011
Model:                        OLS    Adj. R-squared:           0.009
Method:                        Least Squares    F-statistic:            4.021
Date:                          Mon, 22 Apr 2024    Prob (F-statistic):      0.0457
Time:                          00:13:34    Log-Likelihood:         -1198.0
No. Observations:              348    AIC:                    2400.
Df Residuals:                  346    BIC:                    2408.
Df Model:                      1
Covariance Type:               nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	1.4425	0.412	3.498	0.001	0.631	2.254
Mkt-RF	0.1881	0.094	2.005	0.046	0.004	0.373

```

=====
Omnibus:                      188.311    Durbin-Watson:           1.764
=====

```



Prob(Omnibus):	0.000	Jarque-Bera (JB):	1789.617
Skew:	2.067	Prob(JB):	0.00
Kurtosis:	13.312	Cond. No.	4.46

Notes:

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

FF3

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.190
Model:	OLS	Adj. R-squared:	0.183
Method:	Least Squares	F-statistic:	26.91
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	1.17e-15
Time:	00:13:34	Log-Likelihood:	-1163.4
No. Observations:	348	AIC:	2335.
Df Residuals:	344	BIC:	2350.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	1.4251	0.375	3.801	0.000	0.688	2.163
Mkt-RF	-0.0007	0.088	-0.008	0.993	-0.174	0.172
SMB	1.0341	0.121	8.514	0.000	0.795	1.273
HML	-0.0022	0.121	-0.018	0.986	-0.240	0.236

Omnibus:	161.889	Durbin-Watson:	1.979
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1257.695
Skew:	1.769	Prob(JB):	7.85e-274
Kurtosis:	11.615	Cond. No.	4.64

Notes:

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

```
[13]: post_DC = eqports[eqports['date'] > '2002-00'].copy()

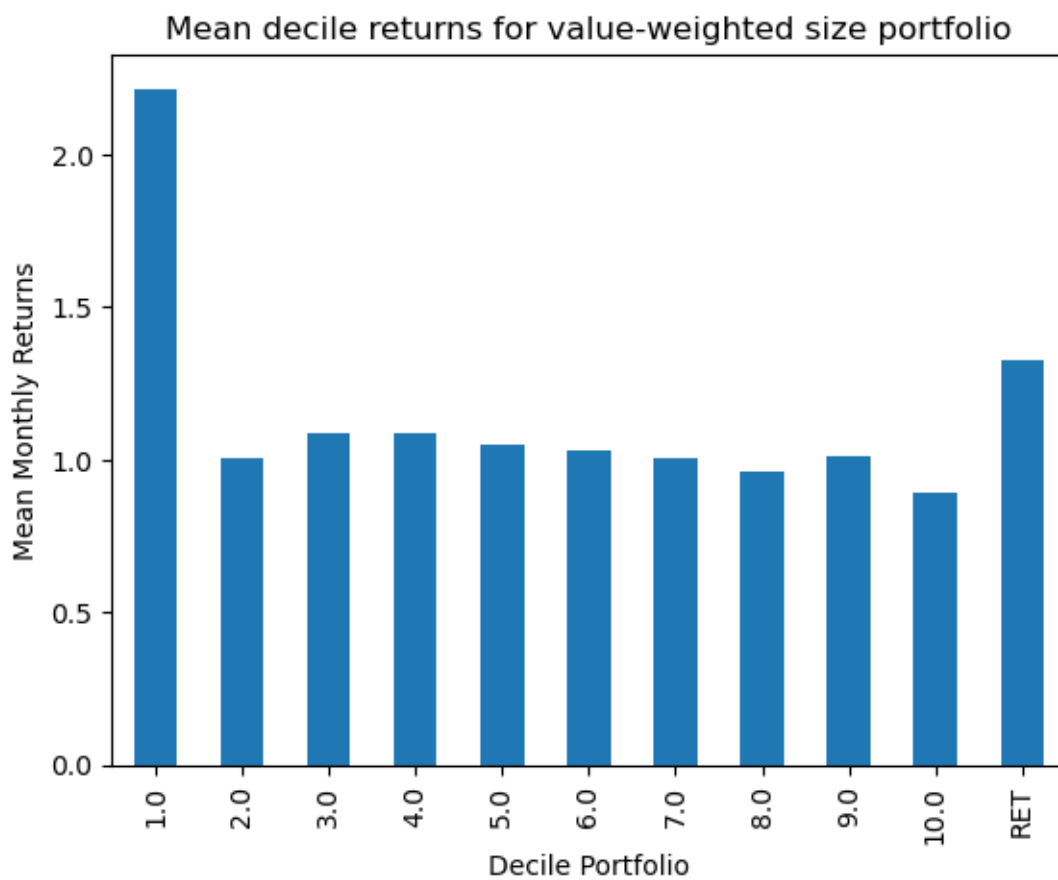
analyze(post_DC, 'Equal-weighted Size', 'RET')
display(post_DC.mean(numeric_only=True))
graph_deciles(post_DC, 'Mean decile returns for value-weighted size portfolio')
estimate_capm_and_ff3(post_DC, 'RET', ff3)
```

Equal-weighted Size monthly returns have mean 1.3233240130717987%, vol 6.181493202819268%, and Sharpe 0.21407837389002618

```

decile_lag
1.0      2.215561
2.0      1.002400
3.0      1.084754
4.0      1.090113
5.0      1.046541
6.0      1.027662
7.0      1.007764
8.0      0.961050
9.0      1.009594
10.0     0.892237
RET      1.323324
dtype: float64

```



CAPM

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:                0.040
Model:                  OLS    Adj. R-squared:             0.036
Method:                 Least Squares    F-statistic:           9.454

```

Date: Mon, 22 Apr 2024 Prob (F-statistic): 0.00237  
Time: 00:13:34 Log-Likelihood: -734.24  
No. Observations: 228 AIC: 1472.  
Df Residuals: 226 BIC: 1479.  
Df Model: 1  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	1.0134	0.409	2.480	0.014	0.208	1.819
Mkt-RF	0.2814	0.092	3.075	0.002	0.101	0.462
Omnibus:	46.372		Durbin-Watson:	1.640		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	73.628		
Skew:	1.133		Prob(JB):	1.03e-16		
Kurtosis:	4.617		Cond. No.	4.53		

Notes:

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

FF3

#### OLS Regression Results

Dep. Variable: y R-squared: 0.142  
Model: OLS Adj. R-squared: 0.130  
Method: Least Squares F-statistic: 12.32  
Date: Mon, 22 Apr 2024 Prob (F-statistic): 1.73e-07  
Time: 00:13:34 Log-Likelihood: -721.50  
No. Observations: 228 AIC: 1451.  
Df Residuals: 224 BIC: 1465.  
Df Model: 3  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.9456	0.390	2.422	0.016	0.176	1.715
Mkt-RF	0.1224	0.094	1.301	0.195	-0.063	0.308
SMB	0.8697	0.169	5.140	0.000	0.536	1.203
HML	-0.0554	0.148	-0.375	0.708	-0.347	0.236
Omnibus:	43.676		Durbin-Watson:	1.768		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	68.040		
Skew:	1.080		Prob(JB):	1.68e-15		
Kurtosis:	4.579		Cond. No.	4.74		

Notes:

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

Comparing the alpha of the size strategy before the 1992 FF paper, after the paper and before the Dot-Com Bubble, and after the Dot-Com Bubble, we conclude that the size strategy still works.

Before the Fama French 1992 paper was published, the CAPM alpha was 1.17 and the FF3 alpha was 0.34, and after the paper the CAPM alpha was 1.44 and the FF3 alpha was 1.42, showing an improvement. Additionally, the graphs of the mean monthly returns of each decile since the publication of the 1992 Fama French paper show that the 1st decile's returns are still larger than that of the 10th decile. So, the size portfolio still works.

We can see that the same still holds for the size factor since the Dot-Com Bubble burst (post-2002), with CAPM alpha of 1.01 and FF3 alpha of 0.95. However, as we can see from the graph, although the 1st decile's mean monthly returns are still higher than the 10th decile's returns, the difference as well as the alpha values are smaller than before. So, while size still works, it does not work as well as before the Bubble.

## 1.4 Problem 3

### 1.4.1 Part A

```
[14]: # Calculate cumulative returns from month t-11 to month t-1
cum_rets = df.groupby('PERMNO')['RET'].rolling(window=11, min_periods=11).
        ↪apply(lambda x: np.prod(1+x)-1).shift(1)
idx = cum_rets.index.get_level_values(1)
cum_rets = pd.Series(cum_rets.values, index=idx).rename('11M_RET')
cum_rets
```

```
[14]: 28          NaN
      29          NaN
      30          NaN
      31          NaN
      32          NaN
      ...
      4705164    5.341741
      4705165    9.344169
      4705166    5.811416
      4705167    4.880464
      4705168    5.784121
      Name: 11M_RET, Length: 2855895, dtype: float64
```

```
[15]: # Merge 11 month rolling returns into df
df_11m_rets = pd.merge(df, cum_rets, left_index=True, right_index=True)
assert(len(df_11m_rets) == len(df))
df_11m_rets = df_11m_rets.dropna(subset=['11M_RET'])
df_11m_rets
```

```
[15]:
```

	PERMNO	date	SHRCD	EXCHCD	PRC	RET	SHROUT	\
41	10001	1987-10	11	3	6.37500	0.020000	992.0	
42	10001	1987-11	11	3	6.18750	-0.029412	992.0	
43	10001	1987-12	11	3	5.87500	-0.033535	992.0	
44	10001	1988-01	11	3	6.25000	0.063830	992.0	
45	10001	1988-02	11	3	6.75000	0.080000	992.0	
...	...	...	...	...	...	...	...	
4705164	93436	2020-08	11	3	498.32001	0.741452	931809.0	
4705165	93436	2020-09	11	3	429.01001	-0.139087	948000.0	
4705166	93436	2020-10	11	3	388.04001	-0.095499	947901.0	
4705167	93436	2020-11	11	3	567.59998	0.462736	947901.0	
4705168	93436	2020-12	11	3	705.66998	0.243252	959854.0	
...	...	...	...	...	...	...	...	
			MV	11M_RET				
41			6.324000e+03	0.169797				
42			6.138000e+03	0.196875				
43			5.828000e+03	0.117836				
44			6.200000e+03	0.022473				
45			6.696000e+03	0.071663				
...			...	...				
4705164			4.643391e+08	5.341741				
4705165			4.067015e+08	9.344169				
4705166			3.678235e+08	5.811416				
4705167			5.380286e+08	4.880464				
4705168			6.773402e+08	5.784121				

[2648337 rows x 9 columns]

```
[16]: # Add deciles
df_11m_rets['rank'] = df_11m_rets.groupby('date')['11M_RET'].rank(pct=True)
df_11m_rets['decile'] = np.ceil(df_11m_rets['rank']*10)

# Use calc_weights helper to get the equal- and value-weighted portfolios
df_weights = df_11m_rets.groupby(['date', 'decile'], group_keys=False).
    .apply(calc_weights)
df_weights['decile_lag'] = df_weights.groupby('PERMNO')['decile'].shift(1)
df_weights['weights_val_lag'] = df_weights.groupby('PERMNO')['weights_val'].
    .shift(1)
df_weights['weights_eq_lag'] = df_weights.groupby('PERMNO')['weights_eq'].
    .shift(1)

# Process final portfolio weights
df_weights = df_weights.drop(['rank', 'decile', 'weights_eq', 'TMV',
    'weights_val'], axis=1)
df_weights
```

```
[16]:
```

	PERMNO	date	SHRCD	EXCHCD	PRC	RET	SHROUT	\
41	10001	1987-10	11	3	6.37500	0.020000	992.0	
42	10001	1987-11	11	3	6.18750	-0.029412	992.0	
43	10001	1987-12	11	3	5.87500	-0.033535	992.0	
44	10001	1988-01	11	3	6.25000	0.063830	992.0	
45	10001	1988-02	11	3	6.75000	0.080000	992.0	
...	...	...	...	...	...	...	...	...
4705164	93436	2020-08	11	3	498.32001	0.741452	931809.0	
4705165	93436	2020-09	11	3	429.01001	-0.139087	948000.0	
4705166	93436	2020-10	11	3	388.04001	-0.095499	947901.0	
4705167	93436	2020-11	11	3	567.59998	0.462736	947901.0	
4705168	93436	2020-12	11	3	705.66998	0.243252	959854.0	

	MV	11M_RET	decile_lag	weights_val_lag	weights_eq_lag
41	6.324000e+03	0.169797	NaN	NaN	NaN
42	6.138000e+03	0.196875	6.0	0.000024	0.002525
43	5.828000e+03	0.117836	9.0	0.000012	0.002538
44	6.200000e+03	0.022473	9.0	0.000013	0.002469
45	6.696000e+03	0.071663	8.0	0.000013	0.002653
...	...	...	...	...	...
4705164	4.643391e+08	5.341741	10.0	0.064252	0.002967
4705165	4.067015e+08	9.344169	10.0	0.071977	0.002959
4705166	3.678235e+08	5.811416	10.0	0.058150	0.002967
4705167	5.380286e+08	4.880464	10.0	0.060722	0.002959
4705168	6.773402e+08	5.784121	10.0	0.185959	0.002941

[2648337 rows x 12 columns]

## 1.4.2 Part B

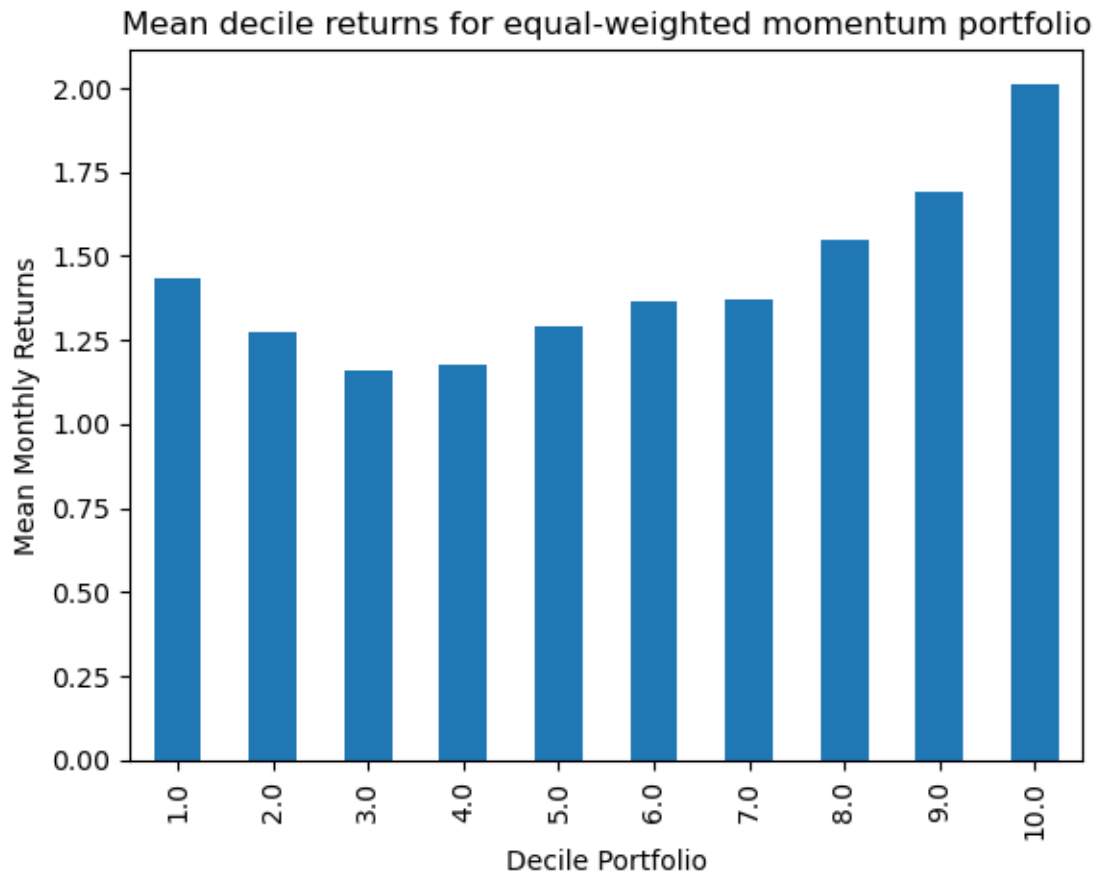
```
[17]: eq_decile_returns, val_decile_returns = part_b(df_weights)

display(eq_decile_returns.mean(numeric_only=True))
graph_deciles(eq_decile_returns, 'Mean decile returns for equal-weighted_
↳momentum portfolio')

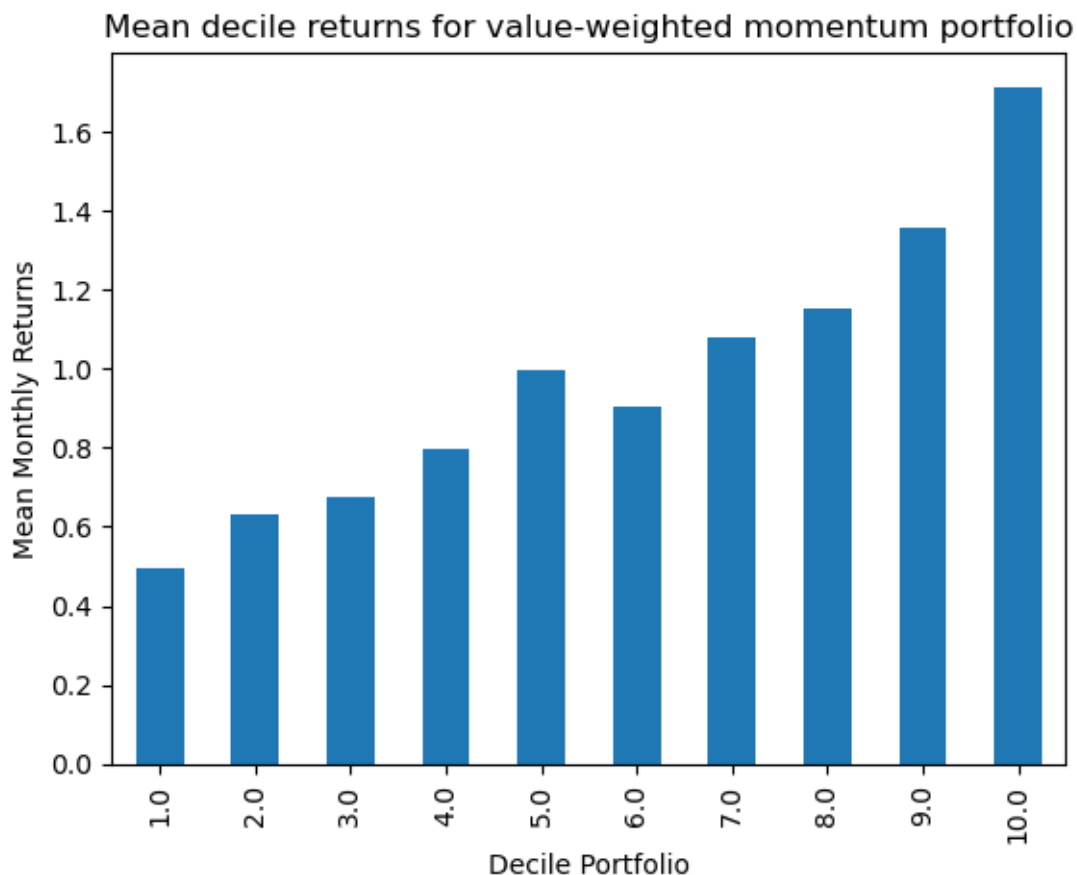
display(val_decile_returns.mean(numeric_only=True))
graph_deciles(val_decile_returns, 'Mean decile returns for value-weighted_
↳momentum portfolio')
```

```
decile_lag
1.0      1.433417
2.0      1.275422
3.0      1.158702
4.0      1.177848
5.0      1.289182
6.0      1.366047
```

```
7.0    1.367513
8.0    1.547550
9.0    1.688353
10.0   2.012180
dtype: float64
```



```
decile_lag
1.0    0.496700
2.0    0.629950
3.0    0.674610
4.0    0.795372
5.0    0.994576
6.0    0.905602
7.0    1.080470
8.0    1.149786
9.0    1.357799
10.0   1.712453
dtype: float64
```



The equal-weighted decile returns are not monotonic, and instead follow a curved pattern where the 10th decile is higher than the 1st decile. The value-weighted decile returns are roughly monotonic, increasing as the decile increases with one exception from the 5th to 6th decile.

### 1.4.3 Part C

```
[18]: analyze(eq_decile_returns, 'Equal-weighted Momentum', 'MOM', reverse=True)
      analyze(val_decile_returns, 'Value-weighted Momentum', 'MOM', reverse=True)
```

Equal-weighted Momentum monthly returns have mean 0.5787633266410294%, vol 10.412249945766787%, and Sharpe 0.055584847622326995

Value-weighted Momentum monthly returns have mean 1.215753149735365%, vol 9.423347313797782%, and Sharpe 0.12901499958037674

### 1.4.4 Part D

```
[19]: print('Equal-Weighted Momentum:')
      print('-----')
      estimate_capm_and_ff3(eq_decile_returns, 'MOM', ff3)
      estimate_ff5(eq_decile_returns, 'MOM', ff5)
```



```

print('\n\n\n\nValue-Weighted Momentum:')
print('-----')
estimate_capm_and_ff3(val_decile_returns, 'MOM', ff3)
estimate_ff5(val_decile_returns, 'MOM', ff5)

# Save momentum returns for part 4
eq_mom_returns = eq_decile_returns[['date', 'MOM']]
val_mom_returns = val_decile_returns[['date', 'MOM']]

```

Equal-Weighted Momentum:

```

-----
--
CAPM

                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.129
Model:                  OLS    Adj. R-squared:            0.129
Method:                 Least Squares    F-statistic:        167.4
Date:                  Mon, 22 Apr 2024    Prob (F-statistic):    8.30e-36
Time:                  00:17:22    Log-Likelihood:        -4166.2
No. Observations:      1129    AIC:                  8336.
Df Residuals:          1127    BIC:                  8346.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.7817	0.291	2.686	0.007	0.211	1.353
Mkt-RF	-0.6967	0.054	-12.940	0.000	-0.802	-0.591

```

=====
Omnibus:                1213.422    Durbin-Watson:          2.003
Prob(Omnibus):           0.000    Jarque-Bera (JB):        126441.503
Skew:                    -5.013    Prob(JB):                0.00
Kurtosis:                53.866    Cond. No.                5.45
=====

```

Notes:

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

FF3

```

                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:                0.343
Model:                  OLS    Adj. R-squared:            0.342
Method:                 Least Squares    F-statistic:        196.1
Date:                  Mon, 22 Apr 2024    Prob (F-statistic):    2.65e-102

```

Time: 00:17:22 Log-Likelihood: -4006.9  
 No. Observations: 1129 AIC: 8022.  
 Df Residuals: 1125 BIC: 8042.  
 Df Model: 3  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	1.0947	0.253	4.319	0.000	0.597	1.592
Mkt-RF	-0.3496	0.051	-6.908	0.000	-0.449	-0.250
SMB	-0.8548	0.083	-10.248	0.000	-1.018	-0.691
HML	-1.1486	0.074	-15.619	0.000	-1.293	-1.004
Omnibus:	797.451		Durbin-Watson:	2.005		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	27077.932		
Skew:	-2.804		Prob(JB):	0.00		
Kurtosis:	26.327		Cond. No.	5.72		

Notes:

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

FF5

#### OLS Regression Results

Dep. Variable: y R-squared: 0.089  
 Model: OLS Adj. R-squared: 0.083  
 Method: Least Squares F-statistic: 13.44  
 Date: Mon, 22 Apr 2024 Prob (F-statistic): 1.62e-12  
 Time: 00:17:22 Log-Likelihood: -2341.8  
 No. Observations: 690 AIC: 4696.  
 Df Residuals: 684 BIC: 4723.  
 Df Model: 5  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.5562	0.288	1.930	0.054	-0.010	1.122
Mkt-RF	-0.1504	0.070	-2.140	0.033	-0.288	-0.012
SMB	-0.2230	0.100	-2.226	0.026	-0.420	-0.026
HML	-0.5734	0.133	-4.310	0.000	-0.835	-0.312
RMW	0.6210	0.139	4.453	0.000	0.347	0.895
CMA	0.4629	0.205	2.254	0.024	0.060	0.866
Omnibus:	419.119		Durbin-Watson:	2.130		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	12101.288		
Skew:	-2.192		Prob(JB):	0.00		
Kurtosis:	23.042		Cond. No.	5.19		

Notes:

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

Value-Weighted Momentum:

CAPM

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.153
Model:	OLS	Adj. R-squared:	0.152
Method:	Least Squares	F-statistic:	203.0
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	1.77e-42
Time:	00:17:22	Log-Likelihood:	-4038.8
No. Observations:	1129	AIC:	8082.
Df Residuals:	1127	BIC:	8092.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	1.4110	0.260	5.428	0.000	0.901	1.921
Mkt-RF	-0.6853	0.048	-14.248	0.000	-0.780	-0.591

Omnibus:	529.207	Durbin-Watson:	1.947
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7027.991
Skew:	-1.808	Prob(JB):	0.00
Kurtosis:	14.676	Cond. No.	5.45

Notes:

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

FF3

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.280
Model:	OLS	Adj. R-squared:	0.278
Method:	Least Squares	F-statistic:	145.6
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	9.96e-80
Time:	00:17:22	Log-Likelihood:	-3947.1
No. Observations:	1129	AIC:	7902.

Df Residuals: 1125 BIC: 7922.  
Df Model: 3  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	1.6345	0.240	6.799	0.000	1.163	2.106
Mkt-RF	-0.4645	0.048	-9.676	0.000	-0.559	-0.370
SMB	-0.4053	0.079	-5.123	0.000	-0.560	-0.250
HML	-0.8953	0.070	-12.837	0.000	-1.032	-0.758
Omnibus:	281.001		Durbin-Watson:		1.955	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		1616.654	
Skew:	-1.018		Prob(JB):		0.00	
Kurtosis:	8.497		Cond. No.		5.72	

Notes:

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

FF5

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.124			
Model:	OLS	Adj. R-squared:	0.117			
Method:	Least Squares	F-statistic:	19.34			
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	4.94e-18			
Time:	00:17:22	Log-Likelihood:	-2410.9			
No. Observations:	690	AIC:	4834.			
Df Residuals:	684	BIC:	4861.			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	1.2522	0.319	3.931	0.000	0.627	1.878
Mkt-RF	-0.4269	0.078	-5.494	0.000	-0.580	-0.274
SMB	-0.0109	0.111	-0.099	0.922	-0.228	0.207
HML	-0.8105	0.147	-5.512	0.000	-1.099	-0.522
RMW	0.6429	0.154	4.171	0.000	0.340	0.946
CMA	0.5730	0.227	2.524	0.012	0.127	1.019
Omnibus:	165.141	Durbin-Watson:	2.013			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	782.467			
Skew:	-1.000	Prob(JB):	1.23e-170			
Kurtosis:	7.818	Cond. No.	5.19			

Notes:

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

Comparing the (CAPM, FF3, and FF5) alphas of the equal-weighted momentum portfolio (0.78, 1.09, 0.56) with those of the value-weighted portfolio (1.41, 1.63, 1.25), it is clear that the value-weighted momentum portfolios have far better alphas. Perhaps the momentum signal is stronger in high value firms.

Under the CAPM model, the FF3 model, and the FF5 model, the alpha that the equal-weighted and value-weighted momentum strategies are generating is statistically significant at the 5% level, with the exception of the equal-weighted FF5 alpha.

As can be seen from the results, the alpha is consistently smaller under the FF5 model, indicating that FF5 does a decent job of pricing momentum. We note a large drop in alpha, especially from the FF3 to the FF5 model, but the alpha does not completely disappear.

### 1.4.5 Part E

We find it likely that the positive momentum alphas are indicative of some unpriced risk. For one, since the momentum papers have been out for a while and this strategy is relatively easy to implement, it stands to reason that the market has priced momentum into the equation already, and that there are many people who have run or are running this strategy.

Second, it is not hard to imagine that a momentum strategy could face extreme risk in many ways: if the portfolio is rebalanced monthly and happens to buy into hot stocks at the start of the month, there is no guarantee that this momentum will carry through the whole month, as just one example.

## 1.5 Problem 4

### 1.5.1 Part A

Notes: Losing ~3000 (<0.1% of) rows since FF website starts July 1926, Professor Sinclair's data starts January 1926. We also assume that once data starts for a given stock, then it continues to be present every month until it stops.

```
[20]: # Merge ff3 data and edit columns
df_merged = pd.merge(df, ff3, how='inner', on=['date'])
df_merged['Ret-RF'] = df_merged['RET']*100 - df_merged['RF']
df_merged = df_merged.drop(['SHRCD', 'EXCHCD', 'PRC', 'SHROUT', 'SMB', 'HML', 'RF'], axis=1)
df_merged
```

```
[20]:
```

	PERMNO	date	RET	MV	Mkt-RF	Ret-RF
0	10001	1986-09	-0.003077	6317.625	-8.60	-0.7577
1	10003	1986-09	-0.057692	40149.375	-8.60	-6.2192
2	10008	1986-09	-0.155963	33867.500	-8.60	-16.0463
3	10009	1986-09	-0.092157	10315.500	-8.60	-9.6657
4	10016	1986-09	-0.020000	224959.000	-8.60	-2.4500
...	...	...	...	...	...	...
2853548	84241	1984-12	0.000000	21850.000	1.84	-0.6400

2853549	85033	1984-12	0.000000	80750.000	1.84	-0.6400
2853550	85762	1984-12	0.093750	110687.500	1.84	8.7350
2853551	89552	1984-12	-0.027778	45543.750	1.84	-3.4178
2853552	90617	1984-12	-0.086420	49052.750	1.84	-9.2820

[2853553 rows x 6 columns]

```
[21]: # Applies the rolling ols and returns the betas where there are enough months
# or np.NaN where there are not enough months
def rolling_ols(group):
    dates = np.array(group['date'])

    if len(group) >= 36:
        y = group['Ret-RF']
        x = sm.add_constant(group['Mkt-RF'])
        model = RollingOLS(y, x, window=36)

        beta_vals = np.array(model.fit().params[['Mkt-RF']].values)
        return np.column_stack((dates, beta_vals))
    else:
        return np.column_stack((dates, np.full(len(group), np.nan)))

# Get the market beta for stock i from time t-36 to time t
beta_i_t = df_merged.groupby('PERMNO').apply(rolling_ols)
beta_i_t = pd.DataFrame(beta_i_t, columns=['beta'])
beta_i_t = beta_i_t.explode('beta')
beta_i_t[['date', 'beta']] = beta_i_t['beta'].apply(lambda el: pd.Series(el))
beta_i_t
```

```
[21]:
```

	beta	date
PERMNO		
10001	NaN	1986-09
10001	NaN	1986-10
10001	NaN	1986-11
10001	NaN	1986-12
10001	NaN	1987-01
...	...	...
93436	1.768065	2020-08
93436	1.847295	2020-09
93436	1.895699	2020-10
93436	2.097154	2020-11
93436	2.120909	2020-12

[2853553 rows x 2 columns]

```
[22]: # Merge betas into df and drop NaN betas
df_betas = pd.merge(df_merged, beta_i_t, how='inner', on=['PERMNO', 'date'])
```

```
assert(len(df_betas) == len(df_merged))
df_betas = df_betas.dropna()
df_betas
```

```
[22]:
```

	PERMNO	date	RET	MV	Mkt-RF	Ret-RF	beta
147437	10001	1990-06	0.014103	10052.2500	-1.09	0.7803	0.025533
147438	10003	1990-06	-0.178571	12615.5000	-1.09	-18.4871	0.883344
147442	10020	1990-06	-0.105357	254355.7500	-1.09	-11.1657	0.186161
147444	10026	1990-06	-0.043478	68763.7500	-1.09	-4.9778	1.741824
147447	10034	1990-06	-0.011111	64013.2500	-1.09	-1.7411	1.057335
...	...	...	...	...	...	...	...
2853546	84180	1984-12	0.045455	22302.8125	1.84	3.9055	1.922804
2853548	84241	1984-12	0.000000	21850.0000	1.84	-0.6400	1.860227
2853549	85033	1984-12	0.000000	80750.0000	1.84	-0.6400	3.746187
2853550	85762	1984-12	0.093750	110687.5000	1.84	8.7350	1.295810
2853551	89552	1984-12	-0.027778	45543.7500	1.84	-3.4178	0.789196

[2191529 rows x 7 columns]

```
[23]: # Add deciles
df_betas['rank'] = df_betas.groupby('date')['beta'].rank(pct=True)
df_betas['decile'] = np.ceil(df_betas['rank']*10)

# Use calc_weights helper to get the equal- and value-weighted portfolios
df_weights = df_betas.groupby(['date', 'decile'], group_keys=False).
    .apply(calc_weights)
df_weights['decile_lag'] = df_weights.groupby('PERMNO')['decile'].shift(1)
df_weights['weights_val_lag'] = df_weights.groupby('PERMNO')['weights_val'].
    .shift(1)
df_weights['weights_eq_lag'] = df_weights.groupby('PERMNO')['weights_eq'].
    .shift(1)

# Process final portfolio weights
df_weights = df_weights.drop(['rank', 'decile', 'weights_eq', 'TMV',
    'weights_val'], axis=1)
df_weights
```

```
[23]:
```

	PERMNO	date	RET	MV	Mkt-RF	Ret-RF	beta \
147437	10001	1990-06	0.014103	10052.2500	-1.09	0.7803	0.025533
147438	10003	1990-06	-0.178571	12615.5000	-1.09	-18.4871	0.883344
147442	10020	1990-06	-0.105357	254355.7500	-1.09	-11.1657	0.186161
147444	10026	1990-06	-0.043478	68763.7500	-1.09	-4.9778	1.741824
147447	10034	1990-06	-0.011111	64013.2500	-1.09	-1.7411	1.057335
...	...	...	...	...	...	...	...
2853546	84180	1984-12	0.045455	22302.8125	1.84	3.9055	1.922804
2853548	84241	1984-12	0.000000	21850.0000	1.84	-0.6400	1.860227
2853549	85033	1984-12	0.000000	80750.0000	1.84	-0.6400	3.746187

2853550	85762	1984-12	0.093750	110687.5000	1.84	8.7350	1.295810
2853551	89552	1984-12	-0.027778	45543.7500	1.84	-3.4178	0.789196

	decile_lag	weights_val_lag	weights_eq_lag
147437	NaN	NaN	NaN
147438	NaN	NaN	NaN
147442	NaN	NaN	NaN
147444	NaN	NaN	NaN
147447	NaN	NaN	NaN
...	...	...	...
2853546	9.0	0.000277	0.003484
2853548	9.0	0.000283	0.003484
2853549	10.0	0.001482	0.003472
2853550	7.0	0.000976	0.002770
2853551	3.0	0.000193	0.003484

[2191529 rows x 10 columns]

## 1.5.2 Part B

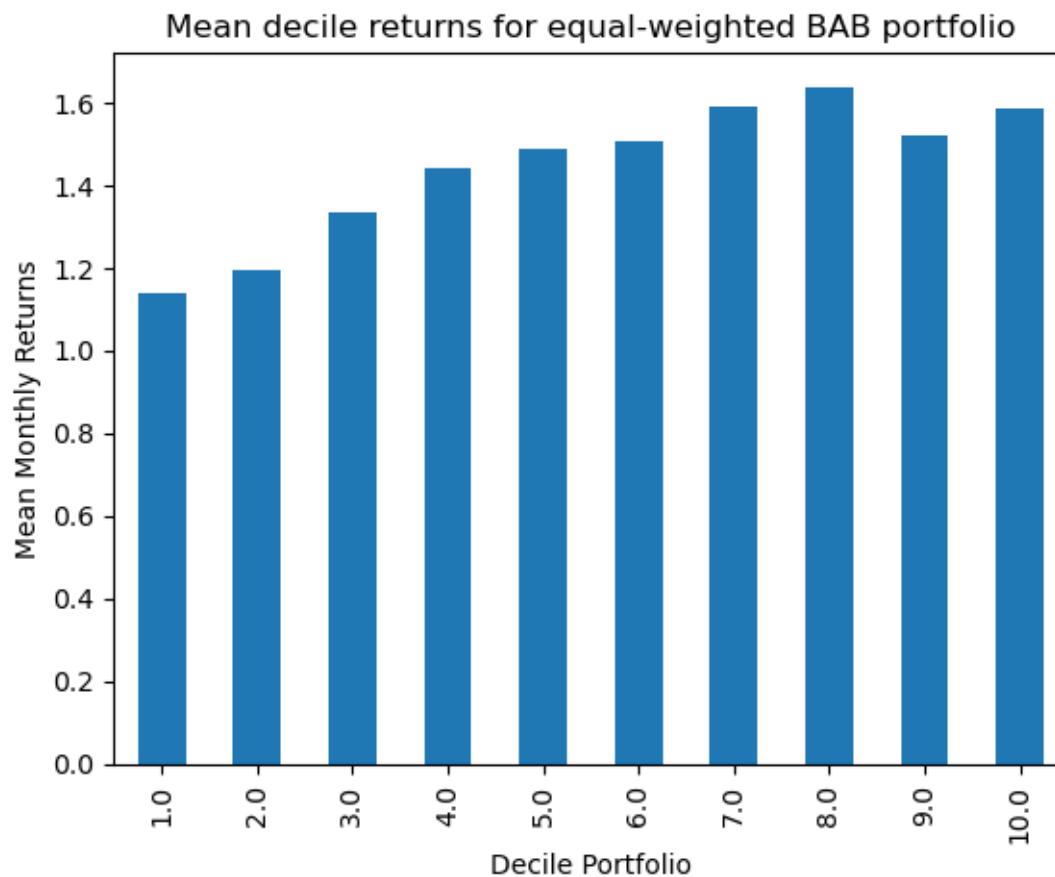
```
[24]: eq_decile_returns, val_decile_returns = part_b(df_weights)

display(eq_decile_returns.mean(numeric_only=True))
graph_deciles(eq_decile_returns, 'Mean decile returns for equal-weighted BAB_
↳portfolio')

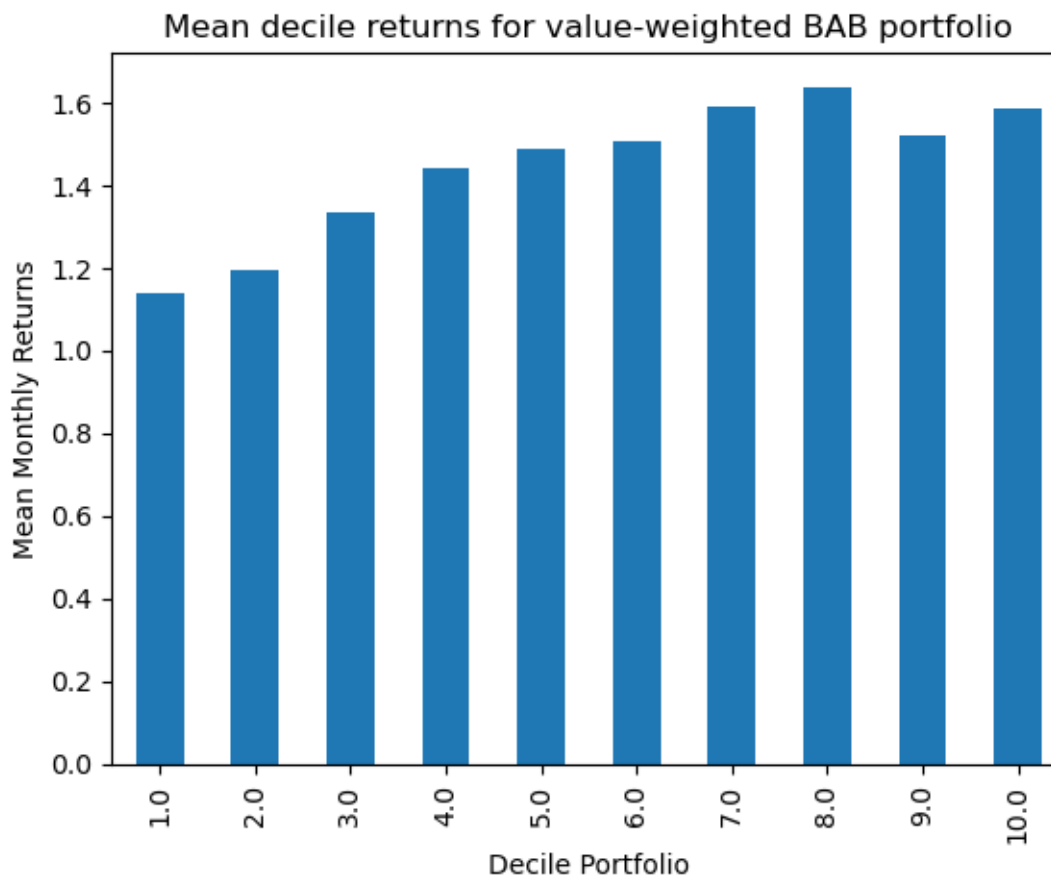
display(val_decile_returns.mean(numeric_only=True))
graph_deciles(eq_decile_returns, 'Mean decile returns for value-weighted BAB_
↳portfolio')
```

```
decile_lag
1.0      1.139108
2.0      1.193500
3.0      1.332549
4.0      1.440455
5.0      1.489458
6.0      1.507843
7.0      1.591752
8.0      1.637702
9.0      1.520740
10.0     1.585494
dtype: float64
```





```
decile_lag
1.0    0.811529
2.0    0.878040
3.0    0.966308
4.0    1.104858
5.0    1.056267
6.0    1.050534
7.0    1.182881
8.0    1.108010
9.0    1.075136
10.0   1.266046
dtype: float64
```



Neither the mean equal-weighted BAB portfolio returns nor the mean value-weighted BAB portfolio returns are perfectly monotonic, though they follow a general upward trend with a plateau around the 6th decile. This makes sense; as the market has gone up on average from 1926, stocks with higher beta would have higher returns on average.

### 1.5.3 Part C

```
[25]: analyze(eq_decile_returns, 'Equal-weighted BAB', 'BAB')
      analyze(val_decile_returns, 'Value-weighted BAB', 'BAB')
```

Equal-weighted BAB monthly returns have mean -0.4463859627601404%, vol 8.364446592723462%, and Sharpe -0.05336706473186975

Value-weighted BAB monthly returns have mean -0.4545175762216238%, vol 8.4328931069834%, and Sharpe -0.05389817829485248

### 1.5.4 Part D

```
[26]: print('Equal-Weighted Betting-Against-Beta:')
print('-----')
estimate_capm_and_ff3(eq_decile_returns, 'BAB', ff3)
estimate_ff5(eq_decile_returns, 'BAB', ff5, add_momentum=True,
             mom_rets=eq_mom_returns)

print('\n\n\n\nValue-Weighted Betting-Against-Beta:')
print('-----')
estimate_capm_and_ff3(val_decile_returns, 'BAB', ff3)
estimate_ff5(val_decile_returns, 'BAB', ff5, add_momentum=True,
             mom_rets=val_mom_returns)
```

Equal-Weighted Betting-Against-Beta:

```
-----
--
CAPM
```

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.538			
Model:	OLS	Adj. R-squared:	0.537			
Method:	Least Squares	F-statistic:	1275.			
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	8.20e-186			
Time:	00:23:34	Log-Likelihood:	-3464.1			
No. Observations:	1098	AIC:	6932.			
Df Residuals:	1096	BIC:	6942.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0673	0.173	0.390	0.697	-0.272	0.406
Mkt-RF	-1.1476	0.032	-35.701	0.000	-1.211	-1.085
Omnibus:	543.422	Durbin-Watson:	1.814			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	6826.466			
Skew:	-1.961	Prob(JB):	0.00			
Kurtosis:	14.569	Cond. No.	5.42			

Notes:

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

FF3

OLS Regression Results		
Dep. Variable:	y	R-squared:
		0.670

```

Model:                OLS      Adj. R-squared:      0.669
Method:               Least Squares  F-statistic:      739.3
Date:                 Mon, 22 Apr 2024  Prob (F-statistic): 1.56e-262
Time:                 00:23:34   Log-Likelihood:    -3279.5
No. Observations:    1098      AIC:                6567.
Df Residuals:        1094      BIC:                6587.
Df Model:             3
Covariance Type:      nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.2418	0.147	1.650	0.099	-0.046	0.529
Mkt-RF	-0.9033	0.030	-30.499	0.000	-0.961	-0.845
SMB	-0.8305	0.048	-17.257	0.000	-0.925	-0.736
HML	-0.4648	0.042	-10.959	0.000	-0.548	-0.382
Omnibus:	390.398		Durbin-Watson:	1.885		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	3758.299		
Skew:	-1.354		Prob(JB):	0.00		
Kurtosis:	11.650		Cond. No.	5.72		

Notes:

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

FF5

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:      0.610
Model:                 OLS    Adj. R-squared:  0.607
Method:               Least Squares  F-statistic:      203.0
Date:                 Mon, 22 Apr 2024  Prob (F-statistic): 5.17e-130
Time:                 00:23:34   Log-Likelihood:    -1815.9
No. Observations:    654      AIC:                3644.
Df Residuals:        648      BIC:                3671.
Df Model:             5
Covariance Type:      nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.3256	0.159	-2.043	0.041	-0.638	-0.013
Mkt-RF	-0.7074	0.040	-17.651	0.000	-0.786	-0.629
SMB	-0.5994	0.055	-10.848	0.000	-0.708	-0.491
HML	0.2353	0.073	3.215	0.001	0.092	0.379
RMW	0.5455	0.076	7.167	0.000	0.396	0.695
CMA	0.1648	0.113	1.456	0.146	-0.058	0.387
Omnibus:	254.102		Durbin-Watson:	1.941		

Prob(Omnibus):	0.000	Jarque-Bera (JB):	2380.543
Skew:	-1.463	Prob(JB):	0.00
Kurtosis:	11.877	Cond. No.	5.08

Notes:

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

FF5 + Momentum

#### OLS Regression Results

Dep. Variable:	y	R-squared:	0.703
Model:	OLS	Adj. R-squared:	0.700
Method:	Least Squares	F-statistic:	255.3
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	7.09e-167
Time:	00:23:34	Log-Likelihood:	-1727.1
No. Observations:	654	AIC:	3468.
Df Residuals:	647	BIC:	3500.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.5475	0.140	-3.908	0.000	-0.823	-0.272
Mkt-RF	-0.6623	0.035	-18.835	0.000	-0.731	-0.593
SMB	-0.5430	0.048	-11.209	0.000	-0.638	-0.448
HML	0.3715	0.065	5.745	0.000	0.245	0.498
RMW	0.3913	0.067	5.808	0.000	0.259	0.524
CMA	0.0534	0.099	0.538	0.591	-0.141	0.248
MOM	0.2574	0.018	14.210	0.000	0.222	0.293

Omnibus:	48.883	Durbin-Watson:	1.898
Prob(Omnibus):	0.000	Jarque-Bera (JB):	143.963
Skew:	-0.328	Prob(JB):	5.48e-32
Kurtosis:	5.203	Cond. No.	8.43

Notes:

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

Value-Weighted Betting-Against-Beta:

-----

--

CAPM

### OLS Regression Results

```

=====
Dep. Variable:                y    R-squared:                0.543
Model:                        OLS  Adj. R-squared:            0.543
Method:                       Least Squares  F-statistic:          1305.
Date:                         Mon, 22 Apr 2024  Prob (F-statistic):    8.32e-189
Time:                         00:23:34    Log-Likelihood:        -3466.1
No. Observations:             1098    AIC:                  6936.
Df Residuals:                 1096    BIC:                  6946.
Df Model:                     1
Covariance Type:              nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0697      0.173        0.403      0.687      -0.270      0.409
Mkt-RF        -1.1632      0.032     -36.119      0.000      -1.226     -1.100
=====

```

```

=====
Omnibus:                208.198    Durbin-Watson:           1.862
Prob(Omnibus):           0.000    Jarque-Bera (JB):        1185.641
Skew:                   -0.743    Prob(JB):                 3.48e-258
Kurtosis:                7.869    Cond. No.                  5.42
=====

```

Notes:

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

FF3

### OLS Regression Results

```

=====
Dep. Variable:                y    R-squared:                0.612
Model:                        OLS  Adj. R-squared:            0.611
Method:                       Least Squares  F-statistic:          575.7
Date:                         Mon, 22 Apr 2024  Prob (F-statistic):    1.93e-224
Time:                         00:23:34    Log-Likelihood:        -3376.5
No. Observations:             1098    AIC:                  6761.
Df Residuals:                 1094    BIC:                  6781.
Df Model:                     3
Covariance Type:              nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.1532      0.160        0.957      0.339      -0.161      0.467
Mkt-RF        -1.0065      0.032     -31.108      0.000      -1.070     -0.943
SMB           -0.7186      0.053     -13.670      0.000      -0.822     -0.615
HML           -0.0926      0.046      -1.999      0.046      -0.184     -0.002
=====

```

```

=====
Omnibus:                192.058    Durbin-Watson:           1.904
Prob(Omnibus):           0.000    Jarque-Bera (JB):        1764.380
=====

```

Skew:	-0.510	Prob(JB):	0.00
Kurtosis:	9.126	Cond. No.	5.72

=====

Notes:

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

FF5

#### OLS Regression Results

=====

Dep. Variable:	y	R-squared:	0.597
Model:	OLS	Adj. R-squared:	0.594
Method:	Least Squares	F-statistic:	192.2
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	2.10e-125
Time:	00:23:34	Log-Likelihood:	-1934.0
No. Observations:	654	AIC:	3880.
Df Residuals:	648	BIC:	3907.
Df Model:	5		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
-----	-----	-----	-----	-----	-----	-----
const	-0.5084	0.191	-2.664	0.008	-0.883	-0.134
Mkt-RF	-0.7893	0.048	-16.441	0.000	-0.884	-0.695
SMB	-0.6070	0.066	-9.172	0.000	-0.737	-0.477
HML	0.3649	0.088	4.161	0.000	0.193	0.537
RMW	0.6802	0.091	7.461	0.000	0.501	0.859
CMA	0.3662	0.136	2.700	0.007	0.100	0.633

=====

Omnibus:	129.386	Durbin-Watson:	1.900
Prob(Omnibus):	0.000	Jarque-Bera (JB):	740.879
Skew:	-0.743	Prob(JB):	1.32e-161
Kurtosis:	7.998	Cond. No.	5.08

=====

Notes:

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

FF5 + Momentum

#### OLS Regression Results

=====

Dep. Variable:	y	R-squared:	0.624
Model:	OLS	Adj. R-squared:	0.621
Method:	Least Squares	F-statistic:	179.1
Date:	Mon, 22 Apr 2024	Prob (F-statistic):	6.65e-134
Time:	00:23:35	Log-Likelihood:	-1911.4
No. Observations:	654	AIC:	3837.
Df Residuals:	647	BIC:	3868.

Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-0.7502	0.188	-3.992	0.000	-1.119	-0.381
Mkt-RF	-0.7201	0.048	-15.154	0.000	-0.813	-0.627
SMB	-0.6105	0.064	-9.540	0.000	-0.736	-0.485
HML	0.4800	0.086	5.553	0.000	0.310	0.650
RMW	0.5872	0.089	6.583	0.000	0.412	0.762
CMA	0.2845	0.132	2.160	0.031	0.026	0.543
MOM	0.1483	0.022	6.801	0.000	0.105	0.191
Omnibus:	62.838		Durbin-Watson:		1.870	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		269.473	
Skew:	-0.310		Prob(JB):		3.05e-59	
Kurtosis:	6.083		Cond. No.		9.65	

Notes:

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

The CAPM and FF3 alphas are generally small and positive, but the alphas become negative when using FF5 and decrease even more when using FF5 + Momentum. Perhaps this can be explained in part due to more sophisticated models like FF5 and FF5 + Momentum taking into account sources of risk that are unaccounted for in simpler models such as CAPM (CAPM may mistakenly incorporate returns due to this risk as alpha instead of beta). With the exception of CAPM, the equal-weighted portfolio has the higher alphas.

### 1.5.5 Part E

Fundamentally, decreasing the proportion of volatility to returns in this strategy requires the use of better hedging and diversification techniques. One thing we might do is minimize our holdings in assets that are highly correlated with one another, diversifying our portfolio by replacing them with assets of a desired beta that have lower correlation with the rest of our portfolio. If we diversify some of our assets but maintain the same or similar beta deciles, we can decrease our volatility and keep our returns roughly constant, resulting in a better Sharpe Ratio.

[ ]: