

# BEM\_114\_PS4

May 19, 2024

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

[ ]: def make_daily_dates(df):
    return [str(item)[:4] + '-' + str(item)[4:6] + '-' + str(item)[6:] for item in df['Unnamed: 0']]

def make_monthly_dates(df):
    return [str(item)[:4] + '-' + str(item)[4:] for item in df['Unnamed: 0']]

[ ]: ff5_daily = pd.read_csv('/content/F-F_Research_Data_5_Factors_2x3_daily.CSV')
mom_daily = pd.read_csv('/content/F-F_Momentum_Factor_daily.CSV')

ff5_monthly = pd.read_csv('/content/F-F_Research_Data_5_Factors_2x3.csv')
mom_monthly = pd.read_csv('/content/F-F_Momentum_Factor.CSV')

ff5_mom_monthly = pd.merge(ff5_monthly, mom_monthly, how = 'inner', on='Unnamed: 0')
ff5_mom_daily = pd.merge(ff5_daily, mom_daily, how = 'inner', on='Unnamed: 0')

ff5_mom_daily['date'] = make_daily_dates(ff5_mom_daily)
ff5_mom_monthly['date'] = make_monthly_dates(ff5_mom_monthly)

ff5_mom_daily.rename(columns = {'Mom': 'Mom'}, inplace = True)
ff5_mom_monthly.rename(columns = {'Mom': 'Mom'}, inplace = True)

aggregate_monthly_data = ff5_mom_monthly.copy()
```

# 1 1B

```
[ ]: factors = ['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA', 'Mom']

for factor in factors:
    ff5_mom_daily[factor + '_rollvar'] = ff5_mom_daily[factor].rolling(window=22,
    min_periods=22).var()
```

```
[ ]: ff5_mom_daily
```

```
[ ]:
      Unnamed: 0  Mkt-RF  SMB  HML  RMW  CMA  RF  Mom  date \
0      19630701   -0.67  0.02 -0.35  0.03  0.13  0.012 -0.21  1963-07-01
1      19630702    0.79 -0.28  0.28 -0.08 -0.21  0.012  0.42  1963-07-02
2      19630703    0.63 -0.18 -0.10  0.13 -0.25  0.012  0.41  1963-07-03
3      19630705    0.40  0.09 -0.28  0.07 -0.30  0.012  0.07  1963-07-05
4      19630708   -0.63  0.07 -0.20 -0.27  0.06  0.012 -0.45  1963-07-08
...
15285   20240322   -0.23 -0.98 -0.53  0.29 -0.37  0.021  0.43  2024-03-22
15286   20240325   -0.26 -0.10  0.88 -0.22 -0.17  0.021 -0.34  2024-03-25
15287   20240326   -0.26  0.10 -0.13 -0.50  0.23  0.021  0.09  2024-03-26
15288   20240327    0.88  1.29  0.91 -0.14  0.58  0.021 -1.34  2024-03-27
15289   20240328    0.10  0.45  0.48 -0.07  0.09  0.021 -0.44  2024-03-28
```

```
      Mkt-RF_rollvar  SMB_rollvar  HML_rollvar  RMW_rollvar  CMA_rollvar \
0      NaN      NaN      NaN      NaN      NaN
1      NaN      NaN      NaN      NaN      NaN
2      NaN      NaN      NaN      NaN      NaN
3      NaN      NaN      NaN      NaN      NaN
4      NaN      NaN      NaN      NaN      NaN
...
15285    0.505910    0.708938    0.458988    0.309487    0.250368
15286    0.349962    0.607054    0.395853    0.307150    0.185330
15287    0.355926    0.601206    0.397961    0.319346    0.186243
15288    0.376593    0.637681    0.421055    0.293502    0.199281
15289    0.375942    0.568274    0.404085    0.226731    0.181229
```

```
      Mom_rollvar
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
...
15285    0.683857
15286    0.517176
15287    0.516868
15288    0.558861
```

15289      0.552656

[15290 rows x 15 columns]

## 2 1C

We can see from the results below that all factors have coefficients on the lagged variance to be significant at the 5% level according to the OLS summaries displayed below.

```
[ ]: # Collapse data to end of month level

ff5_mom_daily['date'] = pd.to_datetime(ff5_mom_daily['date'])
ff5_mom_daily.set_index('date', inplace = True)
end_of_month_data = ff5_mom_daily.resample('M').last()
# end_of_month_data = ff5_mom_daily.resample('M').mean()

[ ]: # Regress on future variance at lagged variance to determine if future variance
     ↪ predicted by initial variance

for factor in factors:
    input = list(end_of_month_data[factor+'_rollvar'][:-1])
    output = list(end_of_month_data[factor+'_rollvar'][1:])
    model1 = sm.OLS(output, sm.add_constant(input)).fit()
    print(factor.upper() + " LAGGED VARIANCE REGRESSION RESULTS:")
    print(model1.summary())
```

MKT-RF LAGGED VARIANCE REGRESSION RESULTS:

### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:                0.207
Model:                  OLS    Adj. R-squared:           0.206
Method:                 Least Squares    F-statistic:        189.9
Date:                   Tue, 14 May 2024    Prob (F-statistic):    1.51e-38
Time:                   21:21:35    Log-Likelihood:       -1519.8
No. Observations:       728    AIC:                  3044.
Df Residuals:           726    BIC:                  3053.
Df Model:                1
Covariance Type:        nonrobust
=====
```

|       | coef   | std err | t      | P> t  | [0.025 | 0.975] |
|-------|--------|---------|--------|-------|--------|--------|
| const | 0.5672 | 0.080   | 7.073  | 0.000 | 0.410  | 0.725  |
| x1    | 0.4553 | 0.033   | 13.781 | 0.000 | 0.390  | 0.520  |

```
=====
Omnibus:                1236.538    Durbin-Watson:           2.071
Prob(Omnibus):           0.000    Jarque-Bera (JB):        725257.224
Skew:                    10.642    Prob(JB):                 0.00
```

Kurtosis: 156.155 Cond. No. 2.78

Notes:

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

SMB LAGGED VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.136
Model:                  OLS    Adj. R-squared:       0.134
Method:                 Least Squares  F-statistic:      114.0
Date:                  Tue, 14 May 2024  Prob (F-statistic): 8.20e-25
Time:                  21:21:35  Log-Likelihood:   -463.72
No. Observations:      728      AIC:              931.4
Df Residuals:          726      BIC:              940.6
Df Model:               1
Covariance Type:        nonrobust
=====
```

|       | coef   | std err | t      | P> t  | [0.025 | 0.975] |
|-------|--------|---------|--------|-------|--------|--------|
| const | 0.1857 | 0.020   | 9.397  | 0.000 | 0.147  | 0.224  |
| x1    | 0.3684 | 0.035   | 10.676 | 0.000 | 0.301  | 0.436  |

```
=====
Omnibus:                1324.074  Durbin-Watson:          2.111
Prob(Omnibus):           0.000    Jarque-Bera (JB):        1503081.930
Skew:                    11.992    Prob(JB):                 0.00
Kurtosis:                 224.307  Cond. No.                 2.25
=====
```

Notes:

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

HML LAGGED VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.562
Model:                  OLS    Adj. R-squared:       0.561
Method:                 Least Squares  F-statistic:      930.5
Date:                  Tue, 14 May 2024  Prob (F-statistic): 3.57e-132
Time:                  21:21:35  Log-Likelihood:   -431.95
No. Observations:      728      AIC:              867.9
Df Residuals:          726      BIC:              877.1
Df Model:               1
Covariance Type:        nonrobust
=====
```

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

|       |        |       |        |       |       |       |
|-------|--------|-------|--------|-------|-------|-------|
| const | 0.0841 | 0.018 | 4.621  | 0.000 | 0.048 | 0.120 |
| x1    | 0.7494 | 0.025 | 30.504 | 0.000 | 0.701 | 0.798 |

=====

|                |         |                   |           |
|----------------|---------|-------------------|-----------|
| Omnibus:       | 737.266 | Durbin-Watson:    | 2.470     |
| Prob(Omnibus): | 0.000   | Jarque-Bera (JB): | 65383.289 |
| Skew:          | 4.399   | Prob(JB):         | 0.00      |
| Kurtosis:      | 48.586  | Cond. No.         | 1.78      |

=====

Notes:

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

RMW LAGGED VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

=====

|                   |                  |                     |           |
|-------------------|------------------|---------------------|-----------|
| Dep. Variable:    | y                | R-squared:          | 0.522     |
| Model:            | OLS              | Adj. R-squared:     | 0.522     |
| Method:           | Least Squares    | F-statistic:        | 793.7     |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 1.43e-118 |
| Time:             | 21:21:35         | Log-Likelihood:     | 111.28    |
| No. Observations: | 728              | AIC:                | -218.6    |
| Df Residuals:     | 726              | BIC:                | -209.4    |
| Df Model:         | 1                |                     |           |
| Covariance Type:  | nonrobust        |                     |           |

=====

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

-----

|       |        |       |        |       |       |       |
|-------|--------|-------|--------|-------|-------|-------|
| const | 0.0438 | 0.009 | 5.035  | 0.000 | 0.027 | 0.061 |
| x1    | 0.7226 | 0.026 | 28.173 | 0.000 | 0.672 | 0.773 |

=====

|                |         |                   |            |
|----------------|---------|-------------------|------------|
| Omnibus:       | 733.346 | Durbin-Watson:    | 2.192      |
| Prob(Omnibus): | 0.000   | Jarque-Bera (JB): | 122814.118 |
| Skew:          | 4.101   | Prob(JB):         | 0.00       |
| Kurtosis:      | 66.099  | Cond. No.         | 3.42       |

=====

Notes:

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

CMA LAGGED VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

=====

|                   |                  |                     |           |
|-------------------|------------------|---------------------|-----------|
| Dep. Variable:    | y                | R-squared:          | 0.473     |
| Model:            | OLS              | Adj. R-squared:     | 0.472     |
| Method:           | Least Squares    | F-statistic:        | 651.3     |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 4.91e-103 |
| Time:             | 21:21:35         | Log-Likelihood:     | 311.80    |
| No. Observations: | 728              | AIC:                | -619.6    |

Df Residuals: 726 BIC: -610.4  
Df Model: 1  
Covariance Type: nonrobust

|                | coef    | std err | t                 | P> t      | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|-----------|--------|--------|
| const          | 0.0441  | 0.007   | 6.324             | 0.000     | 0.030  | 0.058  |
| x1             | 0.6876  | 0.027   | 25.520            | 0.000     | 0.635  | 0.740  |
| Omnibus:       | 518.536 |         | Durbin-Watson:    | 2.343     |        |        |
| Prob(Omnibus): | 0.000   |         | Jarque-Bera (JB): | 27642.076 |        |        |
| Skew:          | 2.579   |         | Prob(JB):         | 0.00      |        |        |
| Kurtosis:      | 32.743  |         | Cond. No.         | 4.70      |        |        |

Notes:

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

MOM LAGGED VARIANCE REGRESSION RESULTS:

OLS Regression Results

|                   |                  |                     |            |       |        |        |
|-------------------|------------------|---------------------|------------|-------|--------|--------|
| Dep. Variable:    | y                | R-squared:          | 0.396      |       |        |        |
| Model:            | OLS              | Adj. R-squared:     | 0.395      |       |        |        |
| Method:           | Least Squares    | F-statistic:        | 476.5      |       |        |        |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 1.33e-81   |       |        |        |
| Time:             | 21:21:35         | Log-Likelihood:     | -1033.1    |       |        |        |
| No. Observations: | 728              | AIC:                | 2070.      |       |        |        |
| Df Residuals:     | 726              | BIC:                | 2079.      |       |        |        |
| Df Model:         | 1                |                     |            |       |        |        |
| Covariance Type:  | nonrobust        |                     |            |       |        |        |
| =====             |                  |                     |            |       |        |        |
|                   | coef             | std err             | t          | P> t  | [0.025 | 0.975] |
| -----             |                  |                     |            |       |        |        |
| const             | 0.2165           | 0.041               | 5.315      | 0.000 | 0.137  | 0.297  |
| x1                | 0.6294           | 0.029               | 21.829     | 0.000 | 0.573  | 0.686  |
| =====             |                  |                     |            |       |        |        |
| Omnibus:          | 807.815          | Durbin-Watson:      | 2.335      |       |        |        |
| Prob(Omnibus):    | 0.000            | Jarque-Bera (JB):   | 103546.383 |       |        |        |
| Skew:             | 5.017            | Prob(JB):           | 0.00       |       |        |        |
| Kurtosis:         | 60.558           | Cond. No.           | 1.76       |       |        |        |
| -----             |                  |                     |            |       |        |        |

Notes:

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

[ ]: ff5\_monthly

```
[ ]:      Unnamed: 0  Mkt-RF  SMB  HML  RMW  CMA  RF
0      196307    -0.39 -0.41 -0.97  0.68 -1.18  0.27
1      196308     5.07 -0.80  1.80  0.36 -0.35  0.25
2      196309    -1.57 -0.52  0.13 -0.71  0.29  0.27
3      196310     2.53 -1.39 -0.10  2.80 -2.01  0.29
4      196311    -0.85 -0.88  1.75 -0.51  2.24  0.27
..      ""      ""      ""      ""      ""      ""
724     202311     8.84 -0.12  1.64 -3.91 -1.00  0.44
725     202312     4.87  7.32  4.93 -3.07  1.32  0.43
726     202401     0.71 -5.74 -2.38  0.69 -0.96  0.47
727     202402     5.06 -0.78 -3.49 -1.99 -2.14  0.42
728     202403     2.83 -1.16  4.19  1.48  1.18  0.43
```

[729 rows x 7 columns]

For all factors, past variance significantly predicts future variance.

### 3 1D

```
[ ]: # Regress at returns for time t on variances at time t - 1 to determine if
      ↪ future returns predicted by variance

for factor in factors:
    input = list(end_of_month_data[factor+'_rollvar'][:-1])
    output = list(ff5_mom_monthly[factor][1:])
    model1 = sm.OLS(output, sm.add_constant(input)).fit()
    print(factor.upper() + " FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:")
    print(model1.summary())
```

MKT-RF FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.000
Model:                OLS      Adj. R-squared:      -0.001
Method:              Least Squares      F-statistic:      0.007564
Date:                Tue, 14 May 2024      Prob (F-statistic):      0.931
Time:                21:24:17      Log-Likelihood:      -2126.6
No. Observations:      728      AIC:          4257.
Df Residuals:          726      BIC:          4266.
Df Model:              1
Covariance Type:      nonrobust
=====
```

|       | coef    | std err | t      | P> t  | [0.025 | 0.975] |
|-------|---------|---------|--------|-------|--------|--------|
| const | 0.5858  | 0.185   | 3.174  | 0.002 | 0.223  | 0.948  |
| x1    | -0.0066 | 0.076   | -0.087 | 0.931 | -0.156 | 0.143  |

```
=====
Omnibus:          58.161      Durbin-Watson:          1.912
```

|                |        |                   |          |
|----------------|--------|-------------------|----------|
| Prob(Omnibus): | 0.000  | Jarque-Bera (JB): | 118.267  |
| Skew:          | -0.493 | Prob(JB):         | 2.08e-26 |
| Kurtosis:      | 4.711  | Cond. No.         | 2.78     |

Notes:

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

SMB FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

|                   |                  |                     |         |
|-------------------|------------------|---------------------|---------|
| Dep. Variable:    | y                | R-squared:          | 0.001   |
| Model:            | OLS              | Adj. R-squared:     | -0.001  |
| Method:           | Least Squares    | F-statistic:        | 0.3840  |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 0.536   |
| Time:             | 21:24:17         | Log-Likelihood:     | -1841.1 |
| No. Observations: | 728              | AIC:                | 3686.   |
| Df Residuals:     | 726              | BIC:                | 3695.   |
| Df Model:         | 1                |                     |         |
| Covariance Type:  | nonrobust        |                     |         |

|       | coef   | std err | t     | P> t  | [0.025 | 0.975] |
|-------|--------|---------|-------|-------|--------|--------|
| const | 0.1626 | 0.131   | 1.241 | 0.215 | -0.095 | 0.420  |
| x1    | 0.1418 | 0.229   | 0.620 | 0.536 | -0.307 | 0.591  |

|                |        |                   |          |
|----------------|--------|-------------------|----------|
| Omnibus:       | 67.382 | Durbin-Watson:    | 1.860    |
| Prob(Omnibus): | 0.000  | Jarque-Bera (JB): | 275.941  |
| Skew:          | 0.317  | Prob(JB):         | 1.20e-60 |
| Kurtosis:      | 5.949  | Cond. No.         | 2.25     |

Notes:

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

HML FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

|                   |                  |                     |         |
|-------------------|------------------|---------------------|---------|
| Dep. Variable:    | y                | R-squared:          | 0.000   |
| Model:            | OLS              | Adj. R-squared:     | -0.001  |
| Method:           | Least Squares    | F-statistic:        | 0.3245  |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 0.569   |
| Time:             | 21:24:17         | Log-Likelihood:     | -1831.8 |
| No. Observations: | 728              | AIC:                | 3668.   |
| Df Residuals:     | 726              | BIC:                | 3677.   |
| Df Model:         | 1                |                     |         |
| Covariance Type:  | nonrobust        |                     |         |



|                | coef    | std err | t                 | P> t  | [0.025 | 0.975]   |
|----------------|---------|---------|-------------------|-------|--------|----------|
| -----          | -----   | -----   | -----             | ----- | -----  | -----    |
| const          | 0.3219  | 0.125   | 2.585             | 0.010 | 0.077  | 0.566    |
| x1             | -0.0957 | 0.168   | -0.570            | 0.569 | -0.426 | 0.234    |
| =====          | =====   | =====   | =====             | ===== | =====  | =====    |
| Omnibus:       |         | 44.049  | Durbin-Watson:    |       |        | 1.661    |
| Prob(Omnibus): |         | 0.000   | Jarque-Bera (JB): |       |        | 158.124  |
| Skew:          |         | 0.105   | Prob(JB):         |       |        | 4.61e-35 |
| Kurtosis:      |         | 5.274   | Cond. No.         |       |        | 1.78     |
| =====          | =====   | =====   | =====             | ===== | =====  | =====    |

Notes:

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

RMW FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

|                   |                  |                     |          |
|-------------------|------------------|---------------------|----------|
| Dep. Variable:    | y                | R-squared:          | 0.018    |
| Model:            | OLS              | Adj. R-squared:     | 0.016    |
| Method:           | Least Squares    | F-statistic:        | 13.19    |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 0.000301 |
| Time:             | 21:24:17         | Log-Likelihood:     | -1608.0  |
| No. Observations: | 728              | AIC:                | 3220.    |
| Df Residuals:     | 726              | BIC:                | 3229.    |
| Df Model:         | 1                |                     |          |
| Covariance Type:  | nonrobust        |                     |          |

|                | coef   | std err | t                 | P> t  | [0.025 | 0.975]   |
|----------------|--------|---------|-------------------|-------|--------|----------|
| -----          | -----  | -----   | -----             | ----- | -----  | -----    |
| const          | 0.1268 | 0.092   | 1.376             | 0.169 | -0.054 | 0.308    |
| x1             | 0.9881 | 0.272   | 3.632             | 0.000 | 0.454  | 1.522    |
| =====          | =====  | =====   | =====             | ===== | =====  | =====    |
| Omnibus:       |        | 209.166 | Durbin-Watson:    |       |        | 1.734    |
| Prob(Omnibus): |        | 0.000   | Jarque-Bera (JB): |       |        | 4104.097 |
| Skew:          |        | -0.771  | Prob(JB):         |       |        | 0.00     |
| Kurtosis:      |        | 14.529  | Cond. No.         |       |        | 3.42     |
| =====          | =====  | =====   | =====             | ===== | =====  | =====    |

Notes:

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

CMA FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

|                |                  |                     |          |
|----------------|------------------|---------------------|----------|
| Dep. Variable: | y                | R-squared:          | 0.022    |
| Model:         | OLS              | Adj. R-squared:     | 0.021    |
| Method:        | Least Squares    | F-statistic:        | 16.48    |
| Date:          | Tue, 14 May 2024 | Prob (F-statistic): | 5.45e-05 |

Time: 21:24:17 Log-Likelihood: -1556.1  
 No. Observations: 728 AIC: 3116.  
 Df Residuals: 726 BIC: 3125.  
 Df Model: 1  
 Covariance Type: nonrobust

|                | coef   | std err | t                 | P> t     | [0.025 | 0.975] |
|----------------|--------|---------|-------------------|----------|--------|--------|
| const          | 0.0712 | 0.091   | 0.785             | 0.432    | -0.107 | 0.249  |
| x1             | 1.4231 | 0.351   | 4.060             | 0.000    | 0.735  | 2.111  |
| Omnibus:       | 23.162 |         | Durbin-Watson:    | 1.774    |        |        |
| Prob(Omnibus): | 0.000  |         | Jarque-Bera (JB): | 51.834   |        |        |
| Skew:          | -0.091 |         | Prob(JB):         | 5.55e-12 |        |        |
| Kurtosis:      | 4.295  |         | Cond. No.         | 4.70     |        |        |

Notes:

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

MOM FUTURE RETURNS ON VARIANCE REGRESSION RESULTS:

#### OLS Regression Results

|                   |                  |                     |           |       |        |        |
|-------------------|------------------|---------------------|-----------|-------|--------|--------|
| Dep. Variable:    | y                | R-squared:          | 0.033     |       |        |        |
| Model:            | OLS              | Adj. R-squared:     | 0.031     |       |        |        |
| Method:           | Least Squares    | F-statistic:        | 24.58     |       |        |        |
| Date:             | Tue, 14 May 2024 | Prob (F-statistic): | 8.88e-07  |       |        |        |
| Time:             | 21:24:17         | Log-Likelihood:     | -2067.5   |       |        |        |
| No. Observations: | 728              | AIC:                | 4139.     |       |        |        |
| Df Residuals:     | 726              | BIC:                | 4148.     |       |        |        |
| Df Model:         | 1                |                     |           |       |        |        |
| Covariance Type:  | nonrobust        |                     |           |       |        |        |
| =====             |                  |                     |           |       |        |        |
|                   | coef             | std err             | t         | P> t  | [0.025 | 0.975] |
| -----             |                  |                     |           |       |        |        |
| const             | 0.9555           | 0.169               | 5.664     | 0.000 | 0.624  | 1.287  |
| x1                | -0.5920          | 0.119               | -4.958    | 0.000 | -0.826 | -0.358 |
| =====             |                  |                     |           |       |        |        |
| Omnibus:          | 162.415          | Durbin-Watson:      | 2.022     |       |        |        |
| Prob(Omnibus):    | 0.000            | Jarque-Bera (JB):   | 1347.295  |       |        |        |
| Skew:             | -0.751           | Prob(JB):           | 2.75e-293 |       |        |        |
| Kurtosis:         | 9.493            | Cond. No.           | 1.76      |       |        |        |

Notes:

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

There is not a consistent pattern between variance in factors and market returns.

## 4 1E

```
[ ]: # # Creating weights

# for factor in factors:
#   mean_var = np.mean(end_of_month_data[factor + '_rollvar'])
#   ff5_mom_monthly[factor + '_weight'] = list(mean_var /
#   ↪end_of_month_data[factor + '_rollvar'])
#   ff5_mom_monthly[factor + '_weight'] = ff5_mom_monthly[factor + '_weight'].
#   ↪shift(1)
#   ff5_mom_monthly[factor + '_rf_weight'] = 1 - ff5_mom_monthly[factor +
#   ↪'_weight']

# # ff5_mom_monthly.head(30)
```

```
[ ]: end_of_month_data.head()
# ff5_mom_monthly.head()
```

```
[ ]:
```

|            | Unnamed: 0 | Mkt-RF | SMB   | HML   | RMW   | CMA   | RF    | Mom   | \ |
|------------|------------|--------|-------|-------|-------|-------|-------|-------|---|
| date       |            |        |       |       |       |       |       |       |   |
| 1963-07-31 | 19630731   | -0.13  | 0.11  | -0.03 | -0.13 | 0.30  | 0.012 | 0.01  |   |
| 1963-08-31 | 19630830   | 0.44   | 0.15  | -0.13 | 0.15  | -0.21 | 0.011 | -0.11 |   |
| 1963-09-30 | 19630930   | -0.60  | 0.21  | 0.08  | 0.24  | 0.13  | 0.014 | -0.56 |   |
| 1963-10-31 | 19631031   | 0.21   | -0.03 | 0.08  | 0.10  | -0.26 | 0.013 | 0.11  |   |
| 1963-11-30 | 19631129   | 1.34   | 0.30  | 0.29  | -0.31 | -0.15 | 0.015 | -0.09 |   |

|            | Mkt-RF_rollvar | SMB_rollvar | HML_rollvar | RMW_rollvar | \ |
|------------|----------------|-------------|-------------|-------------|---|
| date       |                |             |             |             |   |
| 1963-07-31 | 0.223726       | 0.020938    | 0.037883    | 0.022160    |   |
| 1963-08-31 | 0.086949       | 0.033653    | 0.039540    | 0.013295    |   |
| 1963-09-30 | 0.154223       | 0.052577    | 0.035055    | 0.028740    |   |
| 1963-10-31 | 0.171368       | 0.077462    | 0.116457    | 0.061698    |   |
| 1963-11-30 | 1.493974       | 0.207698    | 0.079971    | 0.092893    |   |

|            | CMA_rollvar | Mom_rollvar |
|------------|-------------|-------------|
| date       |             |             |
| 1963-07-31 | 0.031652    | 0.077050    |
| 1963-08-31 | 0.023129    | 0.047702    |
| 1963-09-30 | 0.028083    | 0.072686    |
| 1963-10-31 | 0.085728    | 0.094405    |
| 1963-11-30 | 0.081876    | 0.639916    |

```
[ ]: # Calculate the long-run average variance for each factor over the entire
#   ↪sample period
```

```

long_run_avg_var = {factor: end_of_month_data[factor + '_rollvar'].mean() for
    ↪ factor in factors}
LEVERAGE = 1.5
LEVERAGE = 1.2
# LEVERAGE = 1
# print(long_run_avg_var)
# Calculate the weights for each factor based on the most recent rolling
    ↪ variance at the end of each month
for factor in factors:
    # The weight for each month is based on the long-run average variance
    ↪ divided by the rolling variance from the end of the previous month

    ff5_mom_monthly[factor + '_weight'] = list(long_run_avg_var[factor] /
    ↪ (end_of_month_data[factor + '_rollvar']))
    # ff5_mom_monthly[factor + '_weight'] = np.minimum(ff5_mom_monthly[factor +
    ↪ '_weight'], LEVERAGE)
    ff5_mom_monthly[factor + '_weight'] = ff5_mom_monthly[factor + '_weight'].
    ↪ shift(1)
    ff5_mom_monthly[factor + '_rf_weight'] = 1 - ff5_mom_monthly[factor +
    ↪ '_weight']

    # print(factor + " weights:")
    # print(ff5_mom_monthly[[factor + '_weight', factor + '_rf_weight']].
    ↪ head(-25))

    # print(factor + " weights:")
    # print()
    # print(ff5_mom_monthly[[factor + '_weight', factor + '_rf_weight']].
    ↪ head(30))

# Due to the shift in calculation, the first row will have NaN weights which
    ↪ should be handled if necessary
# print(end_of_month_data.head())
# ff5_mom_monthly.head(10)

```

```
[ ]: print(ff5_mom_monthly['Mom_weight'])
```

```

0      NaN
1      7.560256
2      12.211626
3      8.014243
4      6.170476
...
724     1.037258
725     0.547110
726     0.723806

```

```

727      1.001564
728      0.652168
Name: Mom_weight, Length: 729, dtype: float64

```

```
[ ]: ff5_mom_monthly[ff5_mom_monthly['Unnamed: 0'] < 202304]
```

```

[ ]:      Unnamed: 0  Mkt-RF  SMB  HML  RMW  CMA  RF  Mom  date  \
0      196307    -0.39 -0.41 -0.97  0.68 -1.18  0.27  0.90  1963-07
1      196308     5.07 -0.80  1.80  0.36 -0.35  0.25  1.01  1963-08
2      196309    -1.57 -0.52  0.13 -0.71  0.29  0.27  0.19  1963-09
3      196310     2.53 -1.39 -0.10  2.80 -2.01  0.29  3.12  1963-10
4      196311    -0.85 -0.88  1.75 -0.51  2.24  0.27 -0.74  1963-11
..      ...      ...  ...  ...  ...  ...  ...  ...
712     202211     4.60 -2.74  1.38  6.38  3.18  0.29 -1.98  2022-11
713     202212    -6.41 -0.15  1.37  0.25  4.20  0.33  4.55  2022-12
714     202301     6.65  4.41 -4.01 -2.44 -4.47  0.35 -16.01  2023-01
715     202302    -2.58  0.66 -0.81  1.01 -1.33  0.34  0.15  2023-02
716     202303     2.51 -6.94 -8.85  2.24 -2.37  0.36 -2.47  2023-03

      Mkt-RF_weight  ...  CMA_weight  CMA_rf_weight  Mom_weight  Mom_rf_weight  \
0                NaN  ...          NaN                NaN                NaN
1      4.648926  ...      4.436600      -3.436600      7.560256      -6.560256
2     11.961976  ...      6.071510      -5.071510     12.211626     -11.211626
3      6.744035  ...      5.000403      -4.000403      8.014243      -7.014243
4      6.069292  ...      1.638058      -0.638058      6.170476      -5.170476
..      ...  ...      ...      ...      ...      ...
712     0.329631  ...      0.290298      0.709702      0.374611      0.625389
713     0.326837  ...      0.159744      0.840256      0.114565      0.885435
714     0.567171  ...      0.318249      0.681751      0.337354      0.662646
715     0.890784  ...      0.373564      0.626436      0.393579      0.606421
716     0.931522  ...      0.240823      0.759177      0.214625      0.785375

      Mkt-RF_return  SMB_return  HML_return  RMW_return  CMA_return  Mom_return
0                NaN          NaN          NaN          NaN          NaN          NaN
1      22.657823    -14.449207    13.905104     1.028684    -2.411960     5.995795
2     -21.740036     -6.610864    -0.911674    -11.293256     0.391430    -0.706930
3      15.396638     -9.075994    -3.423037    13.989730    -11.210927    22.970309
4      -6.527607     -4.081592     4.511355    -1.713134     3.496974    -5.962181
..      ...      ...      ...      ...      ...      ...
712     1.710710     -3.021643     0.824265     1.877965     1.128962    -0.560366
713     -1.872884     -0.248597     0.612366     0.309848     0.948211     0.813462
714     3.923179     7.035222    -1.406490    -0.784840    -1.183962    -5.169108
715     -2.261088     0.781287    -0.503209     0.688619    -0.283852     0.265220
716     2.362772     -5.681699    -3.064905     1.427898    -0.297446    -0.247389

```

```
[717 rows x 27 columns]
```

```
[ ]: # Creating returns
print(ff5_mom_monthly['Mkt-RF'].mean())
for factor in factors:
    ff5_mom_monthly[factor + '_return'] = (ff5_mom_monthly[factor] *
    ff5_mom_monthly[factor + '_weight'])
    # print(factor + " mean returns: " + str(np.mean(ff5_mom_monthly[factor +
    '_return'])))
    # print(factor + " reg returns: " + str(np.mean(ff5_mom_monthly[factor])))

    # print(ff5_mom_monthly[["date", factor, factor + '_weight', factor +
    '_return', "RF"]].head(5))
    # print()
```

0.5775582990397805

## 5 1F

```
[ ]: 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("CAPM ESTIMATES")
    # print(model1.summary())
    # print(f'alpha: {model1.params["const"]}')
    conf_int = model1.conf_int(alpha=0.05) # Default is 95% confidence interval
    alpha_conf_int = conf_int.loc["const"] # Confidence interval for the alpha

    # Print the results including the 95th percentile bounds for alpha
    # print("FF5 + MOMENTUM ESTIMATES")
    print(f'alpha: {round(alpha, 3)}')
    print(f'Alpha 95% Confidence Interval: {round(alpha_conf_int[0], 3)} to
    {round(alpha_conf_int[1], 3)}')

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("FF3 ESTIMATES")
    # print(model1.summary())
    # print(f'alpha: {model1.params["const"]}')

    conf_int = model1.conf_int(alpha=0.05) # Default is 95% confidence interval
    alpha_conf_int = conf_int.loc["const"] # Confidence interval for the alpha

    # Print the results including the 95th percentile bounds for alpha
    # print("FF5 + MOMENTUM ESTIMATES")
    print(f'alpha: {round(alpha, 3)}')
```

```

print(f'Alpha 95% Confidence Interval: {round(alpha_conf_int[0], 3)} to
↳{round(alpha_conf_int[1], 3)}')

# 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("FF5 + MOMENTUM ESTIMATES")
#     print(f'alpha: {model1.params["const"]}')
#     print(model1.summary())

def estim_FF5mom(portfolio_ret, data_unique_dates):
    # Running the regression with Fama-French 5 Factors + Momentum
    model1 = sm.OLS(portfolio_ret, sm.add_constant(data_unique_dates[['Mkt-RF',
↳'SMB', 'HML', 'RMW', 'CMA', 'Mom']])).fit()
    alpha = model1.params["const"]

    # Extract the 95% confidence interval for the alpha
    conf_int = model1.conf_int(alpha=0.05) # Default is 95% confidence interval
    alpha_conf_int = conf_int.loc["const"] # Confidence interval for the alpha

    # Print the results including the 95th percentile bounds for alpha
    print("FF5 + MOMENTUM ESTIMATES")
    print(f'alpha: {round(alpha, 3)}')
    print(f'Alpha 95% Confidence Interval: {round(alpha_conf_int[0], 3)} to
↳{round(alpha_conf_int[1], 3)}')
    # print(model1.summary())

```

```
[ ]: # Run models on each factor
```

```

for factor in factors:
    print(factor.upper() + " MODEL ESTIMATION RESULTS:")
    estim_CAPM(ff5_mom_monthly[factor + '_return'].dropna(), ff5_mom_monthly.
↳dropna())
    estim_FF3(ff5_mom_monthly[factor + '_return'].dropna(), ff5_mom_monthly.
↳dropna())
    estim_FF5mom(ff5_mom_monthly[factor + '_return'].dropna(), ff5_mom_monthly.
↳dropna())
    print("-----")

```

MKT-RF MODEL ESTIMATION RESULTS:

CAPM ESTIMATES

alpha: 0.494

Alpha 95% Confidence Interval: -0.113 to 1.1

FF3 ESTIMATES

alpha: 0.468

Alpha 95% Confidence Interval: -0.144 to 1.08

FF5 + MOMENTUM ESTIMATES

alpha: 0.077

Alpha 95% Confidence Interval: -0.551 to 0.704

-----  
SMB MODEL ESTIMATION RESULTS:

CAPM ESTIMATES

alpha: 0.136

Alpha 95% Confidence Interval: -0.418 to 0.689

FF3 ESTIMATES

alpha: -0.04

Alpha 95% Confidence Interval: -0.451 to 0.371

FF5 + MOMENTUM ESTIMATES

alpha: -0.21

Alpha 95% Confidence Interval: -0.634 to 0.214

-----  
HML MODEL ESTIMATION RESULTS:

CAPM ESTIMATES

alpha: 1.13

Alpha 95% Confidence Interval: 0.436 to 1.823

FF3 ESTIMATES

alpha: 0.401

Alpha 95% Confidence Interval: -0.153 to 0.956

FF5 + MOMENTUM ESTIMATES

alpha: 0.764

Alpha 95% Confidence Interval: 0.212 to 1.316

-----  
RMW MODEL ESTIMATION RESULTS:

CAPM ESTIMATES

alpha: 0.874

Alpha 95% Confidence Interval: 0.492 to 1.256

FF3 ESTIMATES

alpha: 1.034

Alpha 95% Confidence Interval: 0.665 to 1.403

FF5 + MOMENTUM ESTIMATES

alpha: 0.604

Alpha 95% Confidence Interval: 0.291 to 0.918

-----  
CMA MODEL ESTIMATION RESULTS:

CAPM ESTIMATES

alpha: 0.533

Alpha 95% Confidence Interval: 0.238 to 0.828

FF3 ESTIMATES

alpha: 0.296

Alpha 95% Confidence Interval: 0.034 to 0.559

FF5 + MOMENTUM ESTIMATES


alpha: 0.199

Alpha 95% Confidence Interval: -0.021 to 0.419  
-----



MOM MODEL ESTIMATION RESULTS:  
 CAPM ESTIMATES  
 alpha: 4.01  
 Alpha 95% Confidence Interval: 2.991 to 5.029  
 FF3 ESTIMATES  
 alpha: 4.202  
 Alpha 95% Confidence Interval: 3.18 to 5.225  
 FF5 + MOMENTUM ESTIMATES  
 alpha: 2.786  
 Alpha 95% Confidence Interval: 1.893 to 3.679

-----

Based on our results, the only strategy that produces consistent and positive alpha across tests is the MOM estimation model. All the other strategies produce either insignificant or negative alpha in some tests. We acknowledge that this is not the result that we anticipated. We believe that the issue here may be related to the uncapped leverage that this implementation of the strategy employs. The way we are calculating the weights as described in the spec allows for this and we believe this is hurting our alpha generation 

## 6 Question 2

```
[ ]: # Invert variance

for factor in factors:
    aggregate_monthly_data[factor+'_invar'] = list(1 / end_of_month_data[factor +
↳ '_rollvar'])

[ ]: # Create weights for each date and shift by 1 since weights at t - 1 determine
↳ returns at t

def create_weights(group):
    columns = [col for col in group.columns if 'invar' in col]

    # Sum the values across the selected columns for each row
    variance_sums = (group[columns].sum(axis=1))

    for factor in factors:
        group[factor + '_weight'] = group[factor + "_invar"] / variance_sums

    return group

aggregate_monthly_data = aggregate_monthly_data.groupby('date').
↳ apply(create_weights)
aggregate_monthly_data = aggregate_monthly_data.reset_index(drop = True)

for factor in factors:
```

```

    aggregate_monthly_data[factor + "_weight"] = aggregate_monthly_data[factor +
↪ '_weight'].shift(1)

aggregate_monthly_data = aggregate_monthly_data.dropna()

```

```
[ ]: # Calculate returns
```

```

def create_returns(group):
    ret = 0
    for factor in factors:
        ret += group[factor] * group[factor + '_weight']

    group['returns'] = ret

    return group

aggregate_monthly_data = aggregate_monthly_data.groupby('date').
↪ apply(create_returns)
aggregate_monthly_data = aggregate_monthly_data.reset_index(drop = True)

```

```
[ ]: # Estimate models on aggregate strategy
```

```

estim_CAPM(aggregate_monthly_data['returns'], aggregate_monthly_data)
estim_FF3(aggregate_monthly_data['returns'], aggregate_monthly_data)
estim_FF5mom(aggregate_monthly_data['returns'], aggregate_monthly_data)

```

CAPM ESTIMATES

alpha: 0.333

Alpha 95% Confidence Interval: 0.257 to 0.41

FF3 ESTIMATES

alpha: 0.251

Alpha 95% Confidence Interval: 0.191 to 0.311

FF5 + MOMENTUM ESTIMATES

alpha: 0.076

Alpha 95% Confidence Interval: 0.033 to 0.119

The aggregate portfolio produced significant alpha, which is better than all the individual portfolios except for the momentum.

```
[ ]: # Calculate cumulative market and strategy portfolio values
```

```

market_rets = list(1 + aggregate_monthly_data['Mkt-RF'] / 100)
strat_rets = list(1 + aggregate_monthly_data['returns'] / 100)

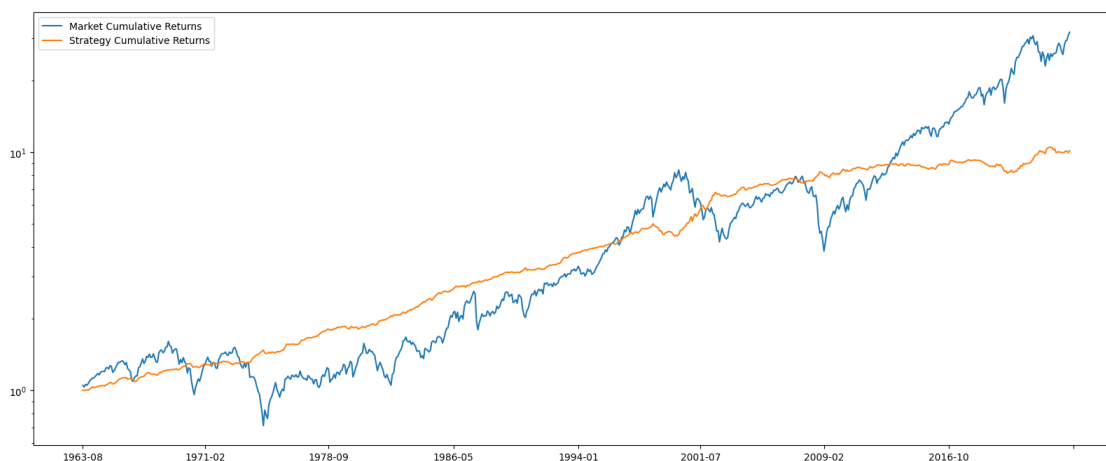
market_cumulative = [1 * np.prod(market_rets[0:i+1]) for i in
↪ range(len(market_rets))]

```

```
strat_cumulative = [1 * np.prod(strat_rets[0:i+1]) for i in
↪range(len(strat_rets))]
```

```
[ ]: import matplotlib.pyplot as plt
from matplotlib.dates import AutoDateLocator

plt.figure(figsize=(20, 8))
x_axis = list(aggregate_monthly_data['date'])
plt.plot(x_axis, market_cumulative, label='Market Cumulative Returns')
plt.plot(x_axis, strat_cumulative, label='Strategy Cumulative Returns')
plt.gca().xaxis.set_major_locator(AutoDateLocator())
plt.gca().set_yscale('log') # Set the y-axis to a logarithmic scale
plt.legend() # Optionally add a legend
plt.show()
```



The volatility managed portfolio produces alpha because it has a lower variance than the market, but a low market beta. Since the turn of the century, the returns have significantly decreased. This is likely due to capital flowing into the strategy, leading to theory behind this strategy being priced into the market.