part-2-updated

October 12, 2023

```
[]: import numpy as np
     import pandas as pd
     from matplotlib import pyplot as plt
     import cvxpy as cp
     from sklearn.linear_model import LinearRegression
[]: raw_data = pd.read_excel('Data.xlsx', sheet_name=None, index_col=0)
[]: data = {}
     sheet_names = list(raw_data.keys())
     for s in sheet_names:
         if s == 'FamaFrenchFactors':
             new_name = s
             col_labels = raw_data[s].columns
         else:
             new_name = s[18:]
             col_labels = range(1, 11)
         data[new_name] = raw_data.pop(s)
         data[new_name].columns = col_labels
         data[new_name].index = (pd.to_datetime(data[new_name].index, format='%Y%m')
                                 .to_period('M').rename('Date'))
```

0.1 Question 3

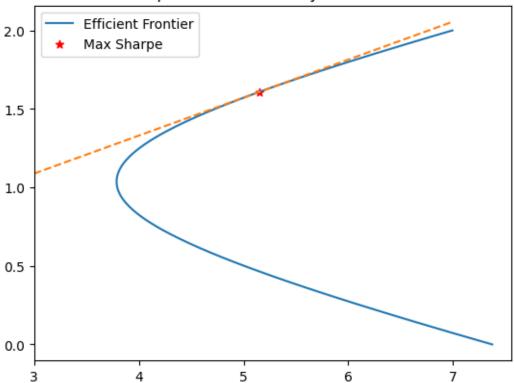
```
class Portfolio:
    def __init__(
        self, mu: pd.Series, S: pd.DataFrame,
        long_only: bool = False,
        ret: float = None, sd: float = None, sharpe: float = None,
        weights: np.ndarray = None
) -> None:
        self.mu = mu
        self.S = S
        self.long_only = long_only
        self.ret = ret
        self.sd = sd
```

```
self.sharpe = sharpe
    self.weights = weights
def optimize_weights(self, target_ret: float = None) -> None:
    w = cp.Variable(self.mu.size)
    ret = self.mu.values @ w
    var = cp.quad_form(w, self.S.values)
    if target ret is not None:
        self.ret = target ret
    elif self.ret is None:
        print("Error: target return not specified")
    if self.long_only:
        prob = cp.Problem(cp.Minimize(var),
                          [cp.sum(w) == 1, ret == self.ret, w >= 0])
    else:
        prob = cp.Problem(cp.Minimize(var),
                          [cp.sum(w) == 1, ret == self.ret])
    var_opt = prob.solve()
    self.ret = float(self.ret)
    self.sd = np.sqrt(var_opt)
    self.weights = np.array(w.value)
def get_sharpe(self, risk_free_rate: float) -> float:
    self.sharpe = (self.ret - risk_free_rate) / self.sd
    return self.sharpe
```

```
p.optimize_weights(target_ret=r)
                 self.portfolios.append(p)
        def get_tan_p(self, risk_free_rate: float) -> Portfolio:
            list_sharpe = []
            for i in range(len(self.ret_range)):
                 list_sharpe.append(self.portfolios[i].get_sharpe(risk_free_rate))
            idx_max_sharpe = np.argmax(np.array(list_sharpe))
            return self.portfolios[idx max sharpe]
        def get_sd_ret_arr(self):
            sd arr = []
            ret_arr = []
            for p in self.portfolios:
                 sd_arr.append(p.sd)
                ret_arr.append(p.ret)
            return (sd_arr, ret_arr)
[]: rf_mu = data['FamaFrenchFactors']['RF'].mean()
    rf mu
[]: 0.36216366158113733
[]: p_inv_mu = data['Investment'].mean()
    p_inv_ex = data['Investment'] - p_inv_mu
    p_inv_S = p_inv_ex.cov()
[]: ef_inv = P_Efficient_Frontier(ret_range=np.linspace(0, 2, 200))
    ef_inv.generate_ef(p_inv_mu, p_inv_S)
    tanp_inv = ef_inv.get_tan_p(risk_free_rate=rf_mu)
[]: tanp_inv.ret, tanp_inv.sd, tanp_inv.sharpe
[]: (1.6080402010050252, 5.147896588073307, 0.2420166213731538)
[]: tanp_inv.weights
[]: array([0.40781556, 0.79465305, 0.52837744, -0.20908625, -0.11511586,
           -0.31282123, 0.3852204, 0.31157557, 0.86795987, -1.65857855])
[]: _, ax = plt.subplots()
    sd_ef_inv, ret_ef_inv = ef_inv.get_sd_ret_arr()
```

```
ax.plot(sd_ef_inv, ret_ef_inv, label='Efficient Frontier')
ax.scatter(tanp_inv.sd, tanp_inv.ret, marker="*", c="r", label="Max Sharpe")
ax.set_xlim(3, )
ax.plot([3, 7],
        [3 * tanp_inv.sharpe + rf_mu, 7 * tanp_inv.sharpe + rf_mu],
        '--')
ax.set_title("10 portfolios formed by investment")
ax.legend()
plt.show()
```

10 portfolios formed by investment

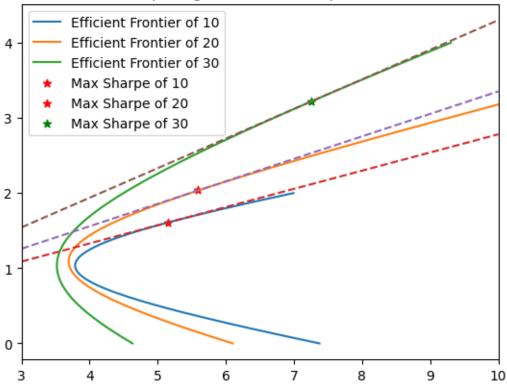


```
[]: p_20_mu = p_20.mean()
p_20_S = (p_20 - p_20_mu).cov()
```

```
[]: ef_20 = P_Efficient_Frontier(ret_range=np.linspace(0, 4, 400))
    ef_20.generate_ef(p_20_mu, p_20_S)
    tanp_20 = ef_20.get_tan_p(risk_free_rate=rf_mu)
[]: tanp_20.ret, tanp_20.sd, tanp_20.sharpe
[]: (2.0350877192982457, 5.593824346035855, 0.2990662477456323)
[]: tanp_20.weights
[]: array([0.78988051, 0.99014918, 0.56167952, 0.58888532, 0.17093563,
           -0.25742778, 0.28170231, 0.31519619, 0.78938115, -0.95186396,
           -0.37081168, -0.60565736, -0.78919639, -0.54669002, 0.44796668,
           -0.75018478, -0.22358038, 0.06362291, 0.63441061, -0.13839766)
[]: p_30 = pd.concat([data['Investment'], data['Profitability'], data['Momentum']],
                     axis=1)
    p_30.columns = ([f'inv_{i}' for i in data['Investment'].columns]
                    + [f'prof_{i}' for i in data['Profitability'].columns]
                    + [f'mom_{i}' for i in data['Momentum'].columns])
[]: p_30_mu = p_30.mean()
    p_30_S = (p_30 - p_30_mu).cov()
[]: ef_30 = P_Efficient_Frontier(ret_range=np.linspace(0, 4, 400))
    ef_30.generate_ef(p_30_mu, p_30_S)
    tanp_30 = ef_30.get_tan_p(risk_free_rate=rf_mu)
[]: tanp_30.ret, tanp_30.sd, tanp_30.sharpe
[]: (3.2180451127819545, 7.250488713684098, 0.3938881314042753)
[]: tanp_30.weights
[]: array([0.47510953, 0.78206432, 0.63087101, 0.36542712, -0.0805739,
           -0.36666614, -0.02724849, -0.11491686, 0.29314728, -1.49698766,
           -0.5103277, -0.55616111, -0.64796704, -0.55649414, 0.67394582,
           -0.79013437, 0.19087547, 0.39121704, 0.45853068, 0.09833374,
           -0.63605413, 0.43168549, 0.9173083, 0.78970808, -0.45781271,
           -0.04901819, -0.52625056, -0.03100014, -0.46699115, 1.81638042])
[]: _, ax = plt.subplots()
    ax.plot(sd_ef_inv, ret_ef_inv, label='Efficient Frontier of 10')
    sd_ef_20, ret_ef_20 = ef_20.get_sd_ret_arr()
    ax.plot(sd_ef_20, ret_ef_20, label='Efficient Frontier of 20')
```

```
sd_ef_30, ret_ef_30 = ef_30.get_sd_ret_arr()
ax.plot(sd_ef_30, ret_ef_30, label='Efficient Frontier of 30')
ax.scatter(tanp_inv.sd, tanp_inv.ret, marker="*", c="r", label="Max Sharpe of_"
→10")
ax.scatter(tanp 20.sd, tanp 20.ret, marker="*", c="r", label="Max Sharpe of 20")
ax.scatter(tanp_30.sd, tanp_30.ret, marker="*", c="g", label="Max Sharpe of 30")
ax.set_xlim(3, )
ax.plot([3, 10],
        [3 * tanp_inv.sharpe + rf_mu, 10 * tanp_inv.sharpe + rf_mu],
        '--')
ax.set_xlim(3, 10)
ax.plot([3, 10],
        [3 * tanp_20.sharpe + rf_mu, 10 * tanp_20.sharpe + rf_mu],
ax.plot([3, 10],
        [3 * tanp_30.sharpe + rf_mu, 10 * tanp_30.sharpe + rf_mu],
ax.set_title("Comparing 10, 20, and 30 portfolios")
ax.legend()
plt.show()
```

Comparing 10, 20, and 30 portfolios



```
[]: df_tanp_30 = pd.DataFrame({
    'mean_return': p_30_mu,
    'sd_return': np.sqrt(np.diag(p_30_S))
})

df_tanp_30['sharpe'] = (df_tanp_30['mean_return'] - rf_mu) /
    df_tanp_30['sd_return']

df_tanp_30['weights'] = tanp_30.weights

df_tanp_30 = df_tanp_30.sort_values(by='weights', ascending=False)
df_tanp_30
```

```
[]:
             mean_return sd_return
                                      sharpe
                                              weights
                1.475284
                          6.118831 0.181917 1.816380
    mom_10
                          5.449894 0.101151 0.917308
    mom_3
                0.913426
    mom_4
                0.942635
                          4.899604 0.118473 0.789708
    inv_2
                          4.750456 0.166122 0.782064
                1.151318
    prof_5
                0.997906
                          4.675570 0.135971 0.673946
    inv_3
                1.067323
                          4.356696 0.161857 0.630871
                          5.358714 0.149621 0.475110
    inv_1
                1.163939
    prof_9
                1.075284
                          4.547001 0.156833 0.458531
```

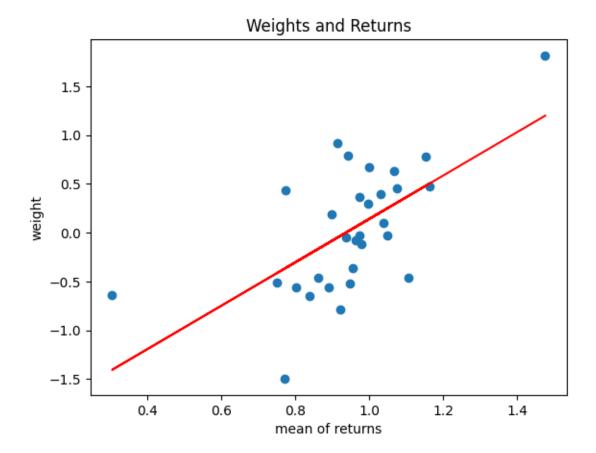
```
prof_8
                 1.030042
                           4.526771
                                     0.147540 0.391217
    inv_4
                 0.973245
                           4.230571
                                     0.144444 0.365427
    inv_9
                 0.997379
                           5.392302
                                     0.117800 0.293147
    prof_7
                 0.898044
                           4.600458 0.116484 0.190875
    prof_10
                 1.038655
                           4.644635
                                     0.145650 0.098334
    inv_7
                           4.400360 0.138738 -0.027248
                0.972663
    mom_8
                 1.049528
                           4.456146 0.154251 -0.031000
    mom 6
                           4.558031 0.126116 -0.049018
                0.937004
    inv_5
                           4.198568 0.142959 -0.080574
                 0.962386
    inv_8
                0.979251
                           4.771906 0.129317 -0.114917
    inv_6
                 0.954660
                           4.390712 0.134943 -0.366666
    mom_5
                0.860333
                           4.498224 0.110748 -0.457813
    mom_9
                 1.106463
                           4.756176 0.156491 -0.466991
    prof_1
                0.748890
                           6.578407 0.058787 -0.510328
                           4.391049 0.132987 -0.526251
    mom_7
                 0.946117
    prof_2
                 0.801942
                           5.189462 0.084744 -0.556161
                           4.616743 0.114265 -0.556494
    prof_4
                0.889695
    mom_1
                 0.304411
                           8.392381 -0.006882 -0.636054
    prof_3
                 0.837323
                           4.939107
                                     0.096204 -0.647967
                                     0.122929 -0.790134
    prof_6
                 0.922080
                           4.554809
    inv_10
                 0.770569
                            6.083457 0.067134 -1.496988
[]: df_tanp_30.corr()
[]:
                 mean_return sd_return
                                            sharpe
                                                    weights
    mean_return
                    1.000000 -0.529972 0.928828 0.631035
    sd return
                    -0.529972
                               1.000000 -0.756718 -0.079825
    sharpe
                    0.928828 -0.756718 1.000000 0.521095
    weights
                    0.631035 -0.079825
                                         0.521095
                                                   1.000000
[]: lm_ret = LinearRegression().fit(df_tanp_30['mean_return'].values.reshape(-1, 1),
                                     df_tanp_30['weights'].values)
    w_pred_ret = lm_ret.predict(df_tanp_30['mean_return'].values.reshape(-1, 1))
    plt.scatter(df tanp 30['mean return'], df tanp 30['weights'])
    plt.plot(df_tanp_30['mean_return'], w_pred_ret, c="r")
    plt.title("Weights and Returns")
    plt.xlabel("mean of returns")
    plt.ylabel("weight")
    plt.show()
```

0.063545 0.431685

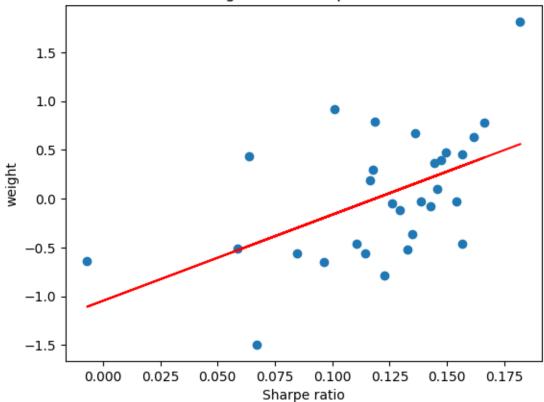
 mom_2

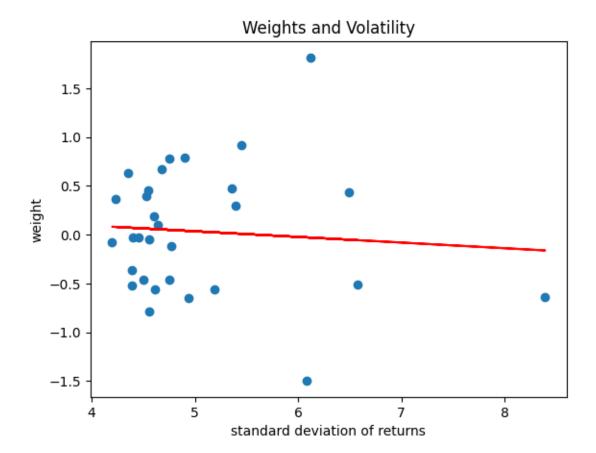
0.774466

6.488377



Weights and Sharpe Ratios

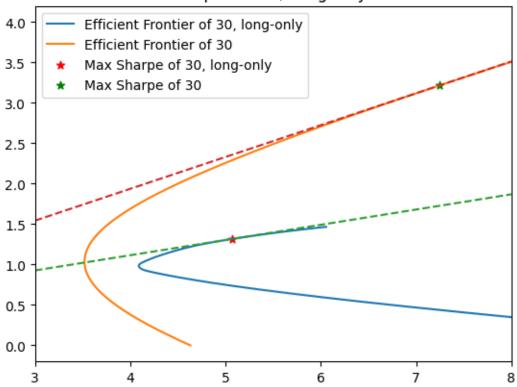




```
[]: ef_30_long = P_Efficient_Frontier(ret_range=np.linspace(0, 2, 200))
     ef_30_long.generate_ef(p_30_mu, p_30_S, long_only=True)
     tanp_30_long = ef_30_long.get_tan_p(risk_free_rate=rf_mu)
[]: tanp_30_long.ret, tanp_30_long.sd, tanp_30_long.sharpe
[]: (1.3165829145728642, 5.065741491751002, 0.18840662409360856)
[]: tanp_30_long.weights.round(decimals=8)
[]: array([-0.
                       , 0.25682331, 0.18506469, -0.
                       , -0.
            -0.
                                    , -0.
                                                  , -0.
                                                                 -0.
            -0.
                                     , -0.
                       , -0.
                                                  , -0.
                                                                 -0.
            -0.
                       , -0.
                                     , -0.
                                                  , -0.
                                                                 -0.
            -0.
                       , -0.
                                    , -0.
                                                  , -0.
                                                                 -0.
            -0.
                                                                  0.55811199])
                       , -0.
                                     , -0.
                                                  , -0.
[]: _, ax = plt.subplots()
     sd_ef_30_long, ret_ef_30_long = ef_30_long.get_sd_ret_arr()
```

```
ax.plot(sd_ef_30_long, ret_ef_30_long,
        label='Efficient Frontier of 30, long-only')
sd_ef_30, ret_ef_30 = ef_30.get_sd_ret_arr()
ax.plot(sd_ef_30, ret_ef_30,
       label='Efficient Frontier of 30')
ax.scatter(tanp_30_long.sd, tanp_30_long.ret, marker="*", c="r",
           label="Max Sharpe of 30, long-only")
ax.scatter(tanp_30.sd, tanp_30.ret, marker="*", c="g",
           label="Max Sharpe of 30")
ax.set_xlim(3, 8)
ax.plot([3, 8],
        [3 * tanp_30_long.sharpe + rf_mu, 8 * tanp_30_long.sharpe + rf_mu],
        !--!)
ax.plot([3, 8],
        [3 * tanp_30.sharpe + rf_mu, 8 * tanp_30.sharpe + rf_mu],
ax.set_title("30 portfolios, Long-only")
ax.legend()
plt.show()
```

30 portfolios, Long-only



```
[]:
             mean_return sd_return
                                      sharpe
                                               weights
                1.475284
                          6.118831 0.181917 0.558112
    mom_10
    inv_2
                1.151318
                          4.750456 0.166122 0.256823
    inv_3
                1.067323
                          4.356696 0.161857 0.185065
    prof_9
                          4.547001 0.156833 -0.000000
                1.075284
    mom_9
                1.106463
                          4.756176 0.156491 -0.000000
    mom_8
                1.049528
                          4.456146 0.154251 -0.000000
    inv_1
                1.163939
                          5.358714 0.149621 -0.000000
    prof_8
                1.030042
                          4.526771 0.147540 -0.000000
```

prof_10	1.038655	4.644635	0.145650	-0.000000
inv_4	0.973245	4.230571	0.144444	-0.000000
inv_5	0.962386	4.198568	0.142959	-0.000000
inv_7	0.972663	4.400360	0.138738	-0.000000
prof_5	0.997906	4.675570	0.135971	-0.000000
inv_6	0.954660	4.390712	0.134943	-0.000000
mom_7	0.946117	4.391049	0.132987	-0.000000
inv_8	0.979251	4.771906	0.129317	-0.000000
mom_6	0.937004	4.558031	0.126116	-0.000000
prof_6	0.922080	4.554809	0.122929	-0.000000
mom_4	0.942635	4.899604	0.118473	-0.000000
inv_9	0.997379	5.392302	0.117800	-0.000000
prof_7	0.898044	4.600458	0.116484	-0.000000
prof_4	0.889695	4.616743	0.114265	-0.000000
mom_5	0.860333	4.498224	0.110748	-0.000000
mom_3	0.913426	5.449894	0.101151	-0.000000
prof_3	0.837323	4.939107	0.096204	-0.000000
prof_2	0.801942	5.189462	0.084744	-0.000000
inv_10	0.770569	6.083457	0.067134	-0.000000
mom_2	0.774466	6.488377	0.063545	-0.000000
prof_1	0.748890	6.578407	0.058787	-0.000000
mom_1	0.304411	8.392381	-0.006882	-0.000000