# QAM project

December 21, 2020

### 1 Import packages

```
[39]: import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt
from pandas.tseries.offsets import MonthEnd, YearEnd
import os
os.chdir("/Users/charlesrambo/Desktop/QIII/QAM project")
```

### 2 Load data

```
[40]: # FF25 portfolio
FF25 = pd.read_csv("FF_25_Portfolios.csv", nrows = 1127)

## Fama-French 3 factor
FF3 = pd.read_csv("FF3.csv")

## Fama-French mom
FFmom = pd.read_csv("FF_Mom.csv")
```

### 3 Clean data

```
[41]: # Record CRISP unknowns
unknowns = ["-66.0", "-77.0", "-88.0", "-99.0", "-99.99", "-999", "A", "B",

→"C", "D", "E", "S", "T", "P"]

# Create function to convert CRISP unknowns to np.nan
convert_unknows = np.vectorize(lambda x: np.nan if x in unknowns else x)

# Convert to decimal
FF25.iloc[:, 1:] = FF25.iloc[:, 1:].apply(convert_unknows, axis = 0).

→astype(float).div(100)
FF3.iloc[:, 1:] =FF3.iloc[:, 1:].apply(convert_unknows, axis = 0).astype(float).

→div(100)
```

```
FFmom.iloc[:, 1] = FFmom.iloc[:, 1].apply(convert_unknows).div(100)
# Rename data columns
FF25.rename(columns = {"Unnamed: 0":"date"}, inplace = True)
FF3.rename(columns = {"Unnamed: 0":"date"}, inplace = True)
FFmom.rename(columns = {"Unnamed: 0":"date"}, inplace = True)
# Convert date column
FF25['date'] = pd.to datetime(FF25['date'], format = "%Y%m")
FF3['date'] = pd.to_datetime(FF3['date'], format = "%Y%m")
FFmom['date'] = pd.to datetime(FFmom['date'], format = "%Y%m")
# Remove the top 5 ME quintiles
ME = []
for i in range(len(FF25.columns)):
   if FF25.columns[i][:3] != 'ME5':
       ME.append(i)
FF25 = FF25.iloc[:, ME]
FF25.drop(['BIG LoBM', 'BIG HiBM'], axis = 1, inplace = True)
```

### 4 Merge data

```
[42]: col4 = FF3.drop('RF', axis = 1)
col5 = FF25.merge(FF3[['date', 'Mkt-RF', 'RF']], on = 'date')
col6 = FF25.merge(FF3, on = 'date').merge(FFmom, on = 'date')
```

#### 5 Excess returns

```
[43]: col5.iloc[:, 1:21] = col5.iloc[:, 1:21].sub(col5['RF'], axis = 0)
col6.iloc[:, 1:21] = col6.iloc[:, 1:21].sub(col6['RF'], axis = 0)

col5.drop('RF', axis = 1, inplace = True)
col6.drop('RF', axis = 1, inplace = True)
```

## 6 Subset date range

```
[44]: start = pd.to_datetime("19899", format = "%Y%m")
end = pd.to_datetime("201912", format = "%Y%m")

col4 = col4.loc[(col4.date >= start) & (col4.date <= end)]
col5 = col5.loc[(col5.date >= start) & (col5.date <= end)]
col6 = col6.loc[(col6.date >= start) & (col6.date <= end)]</pre>
```

### 7 Create function

```
[89]: def get_info(data, M):
          # define X
          X = data.loc[:, data.columns != "date"]
          # define N
          N = len(X.columns)
          # Define table
          table = pd.DataFrame(0, columns = ['mean', 'std', 'Sharpe', 'ceq', |

¬'turn_over'], index = ['ew', 'vw', 'mve_in', 'mve_out', 'shrink_mve_out',

        'rp'])
          # ==== Equal weighting ====
          table.loc['ew', 'mean'] = X.apply(np.mean, axis = 1).mean()
          table.loc['ew', 'std'] = X.apply(np.mean, axis = 1).std()
          table.loc['ew', 'Sharpe'] = table.loc['ew', 'mean']/table.loc['ew', 'std']
          table.loc['ew', 'ceq'] = table.loc['ew', 'mean'] - 0.5 * table.loc['ew', u
       →'std']**2
          # Get turn over
          turn_over = np.zeros(len(X))
          for i in range(len(X)):
              total = 1 + X.iloc[i - 1, :].mean()
              if i == 0:
                  turn_over[i] = 1
              else:
                  turn_over[i] = 1/N * np.absolute(1 - (1 + X.iloc[i - 1, :])/total).
       →sum()
          table.loc['ew', 'turn_over'] = turn_over.mean()
          # === Value weighting ===
          table.loc['vw', 'mean'] = X['Mkt-RF'].mean()
          table.loc['vw', 'std'] = X['Mkt-RF'].std()
          table.loc['vw', 'Sharpe'] = table.loc['vw', 'mean']/table.loc['vw', 'std']
          table.loc['vw', 'turn_over'] = 0
          table.loc['vw', 'ceq'] = table.loc['vw', 'mean'] - 0.5 * table.loc['vw',
       # === MVE in-sample ===
          Sigma = X.cov()
          mu = X.mean()
          w = np.linalg.pinv(Sigma) @ mu/(np.ones(N).T @ np.linalg.pinv(Sigma) @ mu)
```

```
if w @ mu > 0:
       table.loc['mve_in', 'mean'] = w @ mu
       table.loc['mve_in', 'std'] = np.sqrt(w.T @ Sigma @ w)
       table.loc['mve_in', 'Sharpe'] = w @ mu/np.sqrt(w @ Sigma @ w.T)
   else:
       table.loc['mve_in', 'mean'] = -w @ mu
       table.loc['mve_in', 'std'] = np.sqrt(w.T @ Sigma @ w)
       table.loc['mve_in', 'Sharpe'] = -w @ mu/np.sqrt(w @ Sigma @ w.T)
   table.loc['mve_in', 'turn_over'] = np.nan
   table.loc['mve_in', 'ceq'] = table.loc['mve_in', 'mean'] - 0.5 * table.
→loc['mve in', 'std']**2
   # === MVE out-sample ===
   outsample = np.zeros(len(X) - M)
   turn over = np.zeros(len(X) - M)
   w = np.zeros(N)
   for i in range(M, len(X)):
       if i == M:
           total = 1
       else:
           total = 1 + outsample[i - M - 1]
       Sigma = X.iloc[(i - M):i, :].cov()
       mu = X.iloc[(i - M):i, :].mean()
       w_new = np.linalg.pinv(Sigma) @ mu/(np.ones(N).T @ np.linalg.
→pinv(Sigma) @ mu)
       turn_over[i - M] = np.sum(np.absolute(w_new - w @ (1 + X.iloc[i - 1, :
→])/total))
       w = w_new
       if w @ mu > 0:
           outsample[i - M] = X.iloc[i, :] @ w
       else:
           outsample[i - M] = -X.iloc[i, :] @ w
   table.loc['mve_out', 'mean'] = np.mean(outsample)
   table.loc['mve_out', 'std'] = np.std(outsample)
   table.loc['mve_out', 'Sharpe'] = np.mean(outsample)/np.std(outsample)
   table.loc['mve_out', 'turn_over'] = turn_over.mean()
   table.loc['mve_out', 'ceq'] = table.loc['mve_out', 'mean'] - 0.5 * table.
→loc['mve_out', 'std']**2
   # === Shrink MVE out-of-sample ===
   outsample = np.zeros(len(X) - M)
   turn_over = np.zeros(len(X) - M)
   w = np.zeros(N)
```

```
for i in range(M, len(X)):
       if i == M:
           total = 1
       else:
           total = 1 + outsample[i - M - 1]
       # Record sample covariance matrix
       S = X.iloc[(i - M):i, :].cov()
       # Define target matrix
       target = np.mean(np.diag(S)) * np.eye(N)
       # Define function to help compute omega2
       f = lambda row: ((X.iloc[row, :] @ X.iloc[row, :].T - S)**2).sum()
       # Compute non-idiosyncratic variance of variance
       omega2 = np.nanmean([f(x) for x in range(M + 1)])/(M - 1)
       # Calculate total variation of variance
       total_var = ((S - target)**2).sum().sum()
       # Calculate idiosyncratic variance of variance
       delta2 = total_var - omega2
       # Compute shrinkage parameter
       beta = np.max([delta2/total_var, 0])
       # Get Sigma_hat
       Sigma = (1 - beta) * target + beta * S
       # Record sample mean
       m = X.iloc[(i - M):i, :].mean()
       # Record target
       target = np.mean(m)
       # Calculate variance of mean estimate
       omega2 = (X.iloc[(i - M):i, :].std()/np.sqrt(M)).mean()
       # Calculate total variance
       total_var = (X.iloc[(i - M):i, :].sub(target, axis = 0)**2).sum().sum()/
\hookrightarrow (M * len(X.columns))
       # Calculate idiosyncratic variance
       delta2 = total_var - omega2
```

```
# Compute shrinkage parameter
       beta = np.max([delta2/total_var, 0])
       # Compute mu estimate
       mu = (1 - beta) * target + beta * m
       w_new = np.linalg.pinv(Sigma) @ mu/(np.ones(N).T @ np.linalg.
→pinv(Sigma) @ mu)
       turn_over[i - M] = np.sum(np.absolute(w_new - w @ (1 + X.iloc[i - 1, :
→])/total))
      w = w new
       if w @ mu > 0:
           outsample[i - M] = X.iloc[i, :] @ w
       else:
           outsample[i - M] = -X.iloc[i, :] @ w
  table.loc['shrink_mve_out', 'mean'] = np.mean(outsample)
  table.loc['shrink_mve_out', 'std'] = np.std(outsample)
  table.loc['shrink_mve_out', 'Sharpe'] = np.mean(outsample)/np.std(outsample)
  table.loc['shrink_mve_out', 'turn_over'] = turn_over.mean()
  table.loc['shrink_mve_out', 'ceq'] = table.loc['shrink_mve_out', 'mean'] -__
→0.5 * table.loc['shrink_mve_out', 'std']**2
   # === RP ===
  returns = np.zeros(len(X) - M)
  turn_over = np.zeros(len(X) - M)
  w = np.zeros(N)
  for i in range(M, len(X)):
       if i == M:
           total = 1
       else:
           total = 1 + returns[i - M - 1]
       sigma = np.sqrt(np.diag(X.iloc[(i - M):i, :].cov()))
       w_new = (1/sigma)/np.sum(1/sigma)
       returns[i - M] = w_new.T @ X.iloc[i, :]
       turn_over[i - M] = np.sum(np.absolute(w_new - w @ (1 + X.iloc[i - 1, :
→])/total))
      w = w_new
  table.loc['rp', 'mean'] = np.mean(returns)
  table.loc['rp', 'std'] = np.std(returns)
  table.loc['rp', 'Sharpe'] = np.mean(returns)/np.std(returns)
  table.loc['rp', 'turn_over'] = turn_over.mean()
  table.loc['rp', 'ceq'] = table.loc['rp', 'mean'] - 0.5 * table.loc['rp', u
→'std']**2
```

```
# === convert non-equal weighted turn-over to relative turn-over ===
# table.iloc[1:, 4] = table.iloc[1:, 4]/table.iloc[0, 4]
return(table)
```

### 8 Solutions

```
[90]: result 4 = get info(col4, 60)
     result_5 = get_info(col5, 60)
     result_6 = get_info(col6, 60)
[91]: result_4
[91]:
                                   std
                                         Sharpe
                                                      ceq turn_over
                        mean
                    0.002909 0.019409 0.149891 0.002721
                                                           0.023718
     ew
                                       0.155488 0.005668
                                                           0.000000
                    0.006558 0.042175
     vw
                    0.004402 0.025830
     mve_in
                                       0.170433 0.004069
                                                                NaN
     mve_out
                    0.003321 0.210896
                                       0.015748 -0.018917
                                                            6.078604
                                       0.096504 0.001596
                                                           1.997636
     shrink_mve_out 0.001763 0.018273
     rp
                    0.002368 0.018359 0.128997 0.002200
                                                           1.996711
[92]:
     result_5
[92]:
                                   std
                                         Sharpe
                                                      ceq turn_over
                        mean
                    0.007769 0.050617 0.153490 0.006488
                                                           0.018814
                    0.006558 0.042175 0.155488 0.005668
                                                           0.000000
     VW
                    0.025654 0.049555
                                      0.517681 0.024426
     mve_in
                                                                NaN
     mve_out
                    0.023020 0.161758 0.142310 0.009937
                                                          32.830331
     shrink_mve_out
                    0.007333 0.047239
                                       0.155231 0.006217
                                                           19.986497
                    0.008547
                              0.050516 0.169190 0.007271
                                                          19.937500
[93]: result_6
[93]:
                        mean
                                   std
                                         Sharpe
                                                      ceq turn_over
                    0.007105 0.044485 0.159727 0.006116
                                                           0.022231
                    0.006558 0.042175 0.155488 0.005668
                                                           0.000000
     VW
     mve_in
                    NaN
                    0.105233 1.733706 0.060698 -1.397635
                                                          46.131542
     mve_out
     shrink_mve_out 0.005015 0.034197 0.146642 0.004430
                                                          22.922215
                    0.007191 0.041462 0.173446 0.006332 22.927632
     rp
```