Sector Grouping Method

August 31, 2022

[1]:
```
#Data Import

import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt

COMPLETE_df = pd.read_csv("Stock Data (2012-2022)/COMPLETE_data.csv", index_col␣
↪= 0, parse_dates = True).dropna()

SPY_df = pd.read_csv("Stock Data (2012-2022)/SPY_data.csv", index_col = 0,␣
↪parse_dates = True).dropna()
```

[2]:
```
#Create the training and testing datasets

TRAINING_df = COMPLETE_df.loc['2012-01-01':'2016-12-31']
PRECOVID_TESTING_df = COMPLETE_df.loc['2017-01-01':'2019-12-31']
COVID_TESTING_df = COMPLETE_df.loc['2020-01-01':'2022-01-01']
```

[3]:
```
#Create a full list of all the ticker symbols and a set of tickers for each␣
↪sector

all_tickers = list(COMPLETE_df.columns)

GOLD_tickers = set(['CDE', 'HL', 'NEM', 'RGLD'])

ENERGY_tickers = set(['COP', 'CVX', 'SHEL', 'XOM'])

HEALTHCARE_tickers = set(['CVS', 'ELV', 'HCA', 'UNH'])

TECH_tickers = set(['AAPL', 'AMZN', 'GOOG', 'MSFT'])

UTILITY_tickers = set(['D', 'DUK', 'NEE', 'SO'])
```

[4]:
```
# Create all possible combinations of a portfolio of 5 stocks

from itertools import combinations
```

```
combs = list(combinations(all_tickers, 5))

#Store only combinations that has exactly one stock per sector in portfolio
portfolios = []

#It is crucial to use set operations to reduce runtime!!
for comb in combs:

    comb_set = set(comb)

    sum_gld = len(set.intersection(set(GOLD_tickers), comb_set))
    sum_energy = len(set.intersection(set(ENERGY_tickers), comb_set))
    sum_utility = len(set.intersection(set(UTILITY_tickers), comb_set))
    sum_healthcare = len(set.intersection(set(HEALTHCARE_tickers), comb_set))
    sum_tech = len(set.intersection(set(TECH_tickers), comb_set))

    if(sum_gld == sum_energy == sum_utility == sum_healthcare == sum_tech == 1):
        portfolios.append(list(comb))


# It is very time consuming to check if every valid portfolio combinations is␣
 ↪in our list of
# portfolios. A great work around for this is to check a couple of values at␣
 ↪random indexes in the
# list and confirm it meets our criteria. Then, check the length of the list of␣
 ↪portfolios and make
# sure it matches up with the amount of portfolios expected (in our case 4^5 =␣
 ↪1024)
len(portfolios)
```

[4]: 1024

[5]:
```
portfolios[:10]
```

[5]:
```
[['COP', 'CDE', 'CVS', 'AAPL', 'D'],
 ['COP', 'CDE', 'CVS', 'AAPL', 'DUK'],
 ['COP', 'CDE', 'CVS', 'AAPL', 'NEE'],
 ['COP', 'CDE', 'CVS', 'AAPL', 'SO'],
 ['COP', 'CDE', 'CVS', 'AMZN', 'D'],
 ['COP', 'CDE', 'CVS', 'AMZN', 'DUK'],
 ['COP', 'CDE', 'CVS', 'AMZN', 'NEE'],
 ['COP', 'CDE', 'CVS', 'AMZN', 'SO'],
 ['COP', 'CDE', 'CVS', 'GOOG', 'D'],
 ['COP', 'CDE', 'CVS', 'GOOG', 'DUK']]
```

[6]:
```
TRAINING_df.head(10)
```

[6]:

Date	COP	CVX	SHEL	XOM	CDE	HL
2012-01-03	39.503304	71.152664	41.390953	55.358418	25.330000	5.446543
2012-01-04	39.316895	71.030167	41.418819	55.371304	25.590000	5.474912
2012-01-05	39.002655	70.333916	40.688267	55.203938	25.840000	5.437089
2012-01-06	38.699070	69.824661	41.134403	54.791969	25.639999	5.342529
2012-01-09	38.848198	70.585335	41.257107	55.036602	25.510000	5.361442
2012-01-10	39.029282	70.308151	41.457867	55.178188	26.510000	5.522188
2012-01-11	38.352886	69.476509	39.991161	54.766220	25.930000	4.359127
2012-01-12	37.687122	67.671425	39.004074	54.547356	26.370001	4.538787
2012-01-13	37.463432	68.393471	38.596989	54.637478	25.760000	4.463141
2012-01-17	37.708431	68.799614	38.836781	55.158894	25.709999	4.519876

Date	NEM	RGLD	CVS	ELV	HCA	UNH
2012-01-03	50.008633	60.809380	32.779312	57.656933	16.601580	43.781525
2012-01-04	49.855579	60.003040	33.000370	57.972462	15.957155	44.419247
2012-01-05	50.024742	60.169575	32.960880	58.424438	16.333073	44.716866
2012-01-06	49.920025	60.975925	32.731953	60.317593	17.138603	44.878410
2012-01-09	49.525307	61.650799	32.992477	60.701366	16.609251	44.827393
2012-01-10	50.467804	62.159149	33.118786	61.579723	17.230659	44.742363
2012-01-11	51.023636	60.152039	33.189842	61.886730	18.258671	45.073978
2012-01-12	51.587505	59.827728	33.276695	61.238621	17.890429	44.954929
2012-01-13	51.063889	59.529743	33.276695	61.323921	18.335388	44.810398
2012-01-17	49.090290	59.827728	33.584587	62.031719	18.427446	45.550144

Date	AAPL	AMZN	GOOG	MSFT	D	DUK
2012-01-03	12.540046	8.9515	16.573130	21.527195	34.734024	40.991581
2012-01-04	12.607436	8.8755	16.644611	22.033812	34.449535	40.801960
2012-01-05	12.747403	8.8805	16.413727	22.258972	34.376755	40.783012
2012-01-06	12.880663	9.1305	16.189817	22.604755	34.026112	40.783012
2012-01-09	12.860233	8.9280	15.503389	22.307230	33.979797	40.707176
2012-01-10	12.906281	8.9670	15.520326	22.387642	33.933487	40.707176
2012-01-11	12.885239	8.9450	15.590563	22.291142	33.854092	40.574451
2012-01-12	12.849866	8.7965	15.682219	22.516306	33.695301	40.346928
2012-01-13	12.801685	8.9210	15.566403	22.717348	33.476974	40.403816
2012-01-17	12.950803	9.0830	15.655818	22.725388	33.609295	40.422771

Date	NEE	SO
2012-01-03	10.976557	27.804970
2012-01-04	10.948627	27.786449
2012-01-05	11.088282	27.749407
2012-01-06	10.970974	27.465359

```
2012-01-09  10.984007  27.755581
2012-01-10  11.032419  27.656775
2012-01-11  11.024973  27.823494
2012-01-12  11.058486  27.854376
2012-01-13  11.008215  27.953171
2012-01-17  11.013803  27.903784
```

0.0.1 Let's try to create the optimal portfolio using the training data

[7]:
```
rets = TRAINING_df.pct_change().dropna()
rets.head(10)
```

[7]:
```
                 COP       CVX      SHEL       XOM       CDE        HL  \
Date
2012-01-04 -0.004719 -0.001722  0.000673  0.000233  0.010265  0.005209
2012-01-05 -0.007992 -0.009802 -0.017638 -0.003023  0.009769 -0.006908
2012-01-06 -0.007784 -0.007241  0.010965 -0.007463 -0.007740 -0.017392
2012-01-09  0.003854  0.010894  0.002983  0.004465 -0.005070  0.003540
2012-01-10  0.004661 -0.003927  0.004866  0.002573  0.039200  0.029982
2012-01-11 -0.017330 -0.011829 -0.035378 -0.007466 -0.021879 -0.210616
2012-01-12 -0.017359 -0.025981 -0.024683 -0.003996  0.016969  0.041215
2012-01-13 -0.005935  0.010670 -0.010437  0.001652 -0.023132 -0.016667
2012-01-17  0.006540  0.005938  0.006213  0.009543 -0.001941  0.012712
2012-01-18  0.009887  0.001031  0.010195  0.008869  0.029560  0.010460

                 NEM      RGLD       CVS       ELV       HCA       UNH  \
Date
2012-01-04 -0.003061 -0.013260  0.006744  0.005473 -0.038817  0.014566
2012-01-05  0.003393  0.002775 -0.001197  0.007796  0.023558  0.006700
2012-01-06 -0.002093  0.013401 -0.006945  0.032403  0.049319  0.003613
2012-01-09 -0.007907  0.011068  0.007959  0.006363 -0.030887 -0.001137
2012-01-10  0.019031  0.008246  0.003828  0.014470  0.037413 -0.001897
2012-01-11  0.011014 -0.032290  0.002146  0.004986  0.059662  0.007412
2012-01-12  0.011051 -0.005392  0.002617 -0.010473 -0.020168 -0.002641
2012-01-13 -0.010150 -0.004981  0.000000  0.001393  0.024871 -0.003215
2012-01-17 -0.038650  0.005006  0.009252  0.011542  0.005021  0.016508
2012-01-18 -0.009681  0.001905  0.013164 -0.007836  0.009992  0.006907

                AAPL      AMZN      GOOG      MSFT         D       DUK  \
Date
2012-01-04  0.005374 -0.008490  0.004313  0.023534 -0.008190 -0.004626
2012-01-05  0.011102  0.000563 -0.013871  0.010219 -0.002113 -0.000464
2012-01-06  0.010454  0.028152 -0.013642  0.015535 -0.010200  0.000000
2012-01-09 -0.001586 -0.022178 -0.042399 -0.013162 -0.001361 -0.001860
2012-01-10  0.003581  0.004368  0.001092  0.003605 -0.001363  0.000000
2012-01-11 -0.001630 -0.002453  0.004525 -0.004310 -0.002340 -0.003260
2012-01-12 -0.002745 -0.016601  0.005879  0.010101 -0.004690 -0.005608
```

```
2012-01-13 -0.003750  0.014153 -0.007385  0.008929 -0.006479  0.001410
2012-01-17  0.011648  0.018159  0.005744  0.000354  0.003953  0.000469
2012-01-18  0.010384  0.042827  0.006889 -0.001062 -0.007283  0.000000

                 NEE        SO
Date
2012-01-04 -0.002544 -0.000666
2012-01-05  0.012755 -0.001333
2012-01-06 -0.010579 -0.010236
2012-01-09  0.001188  0.010567
2012-01-10  0.004408 -0.003560
2012-01-11 -0.000675  0.006028
2012-01-12  0.003040  0.001110
2012-01-13 -0.004546  0.003547
2012-01-17  0.000508 -0.001767
2012-01-18  0.005917  0.005753
```

[8]:
```python
rets.corr()
```

[8]:
```
           COP       CVX      SHEL       XOM       CDE        HL       NEM  \
COP   1.000000  0.746447  0.649418  0.659882  0.257611  0.258844  0.206732
CVX   0.746447  1.000000  0.708590  0.799605  0.272247  0.280754  0.270671
SHEL  0.649418  0.708590  1.000000  0.664403  0.281361  0.290978  0.259745
XOM   0.659882  0.799605  0.664403  1.000000  0.243499  0.254579  0.243046
CDE   0.257611  0.272247  0.281361  0.243499  1.000000  0.793637  0.710384
HL    0.258844  0.280754  0.290978  0.254579  0.793637  1.000000  0.733497
NEM   0.206732  0.270671  0.259745  0.243046  0.710384  0.733497  1.000000
RGLD  0.181809  0.198367  0.254180  0.194982  0.700122  0.743829  0.763632
CVS   0.249472  0.316133  0.292204  0.341568  0.100592  0.072908  0.074650
ELV   0.250599  0.282596  0.230673  0.315610  0.035189  0.043297  0.026899
HCA   0.221031  0.248354  0.226279  0.233239  0.122564  0.095780  0.048317
UNH   0.246887  0.311814  0.251531  0.319621  0.061268  0.087699  0.049600
AAPL  0.222111  0.270697  0.232800  0.253850  0.130833  0.128528  0.093463
AMZN  0.217184  0.276518  0.239061  0.273477  0.077185  0.092338  0.069135
GOOG  0.229985  0.277249  0.246078  0.296300  0.079344  0.104676  0.033957
MSFT  0.305670  0.379194  0.339819  0.368528  0.133060  0.130525  0.102980
D     0.206763  0.323054  0.280743  0.354410  0.147192  0.156730  0.166485
DUK   0.146809  0.249153  0.197797  0.285481  0.163814  0.170145  0.203352
NEE   0.172388  0.279951  0.220610  0.316837  0.169011  0.179119  0.172118
SO    0.115809  0.216673  0.170317  0.256439  0.134218  0.145209  0.175653

          RGLD       CVS       ELV       HCA       UNH      AAPL      AMZN  \
COP   0.181809  0.249472  0.250599  0.221031  0.246887  0.222111  0.217184
CVX   0.198367  0.316133  0.282596  0.248354  0.311814  0.270697  0.276518
SHEL  0.254180  0.292204  0.230673  0.226279  0.251531  0.232800  0.239061
XOM   0.194982  0.341568  0.315610  0.233239  0.319621  0.253850  0.273477
CDE   0.700122  0.100592  0.035189  0.122564  0.061268  0.130833  0.077185
```

```
HL    0.743829  0.072908  0.043297  0.095780  0.087699  0.128528  0.092338
NEM   0.763632  0.074650  0.026899  0.048317  0.049600  0.093463  0.069135
RGLD  1.000000  0.067471  0.027014  0.083322  0.069734  0.098145  0.037152
CVS   0.067471  1.000000  0.326558  0.265183  0.385239  0.229358  0.241914
ELV   0.027014  0.326558  1.000000  0.256127  0.674135  0.189204  0.197879
HCA   0.083322  0.265183  0.256127  1.000000  0.325121  0.159286  0.172751
UNH   0.069734  0.385239  0.674135  0.325121  1.000000  0.262275  0.230905
AAPL  0.098145  0.229358  0.189204  0.159286  0.262275  1.000000  0.235724
AMZN  0.037152  0.241914  0.197879  0.172751  0.230905  0.235724  1.000000
GOOG  0.044446  0.290688  0.234414  0.237318  0.277607  0.316216  0.486876
MSFT  0.092516  0.314078  0.291787  0.256991  0.315360  0.322843  0.352186
D     0.191579  0.308841  0.209133  0.157729  0.260571  0.132074  0.181637
DUK   0.218755  0.266148  0.147534  0.117578  0.171502  0.101453  0.147083
NEE   0.188895  0.322733  0.207256  0.183134  0.244246  0.140241  0.181155
SO    0.198835  0.253231  0.147229  0.094797  0.192625  0.098248  0.135920

          GOOG      MSFT         D       DUK       NEE        SO
COP   0.229985  0.305670  0.206763  0.146809  0.172388  0.115809
CVX   0.277249  0.379194  0.323054  0.249153  0.279951  0.216673
SHEL  0.246078  0.339819  0.280743  0.197797  0.220610  0.170317
XOM   0.296300  0.368528  0.354410  0.285481  0.316837  0.256439
CDE   0.079344  0.133060  0.147192  0.163814  0.169011  0.134218
HL    0.104676  0.130525  0.156730  0.170145  0.179119  0.145209
NEM   0.033957  0.102980  0.166485  0.203352  0.172118  0.175653
RGLD  0.044446  0.092516  0.191579  0.218755  0.188895  0.198835
CVS   0.290688  0.314078  0.308841  0.266148  0.322733  0.253231
ELV   0.234414  0.291787  0.209133  0.147534  0.207256  0.147229
HCA   0.237318  0.256991  0.157729  0.117578  0.183134  0.094797
UNH   0.277607  0.315360  0.260571  0.171502  0.244246  0.192625
AAPL  0.316216  0.322843  0.132074  0.101453  0.140241  0.098248
AMZN  0.486876  0.352186  0.181637  0.147083  0.181155  0.135920
GOOG  1.000000  0.426986  0.185778  0.162358  0.232862  0.156748
MSFT  0.426986  1.000000  0.293206  0.224440  0.269408  0.224879
D     0.185778  0.293206  1.000000  0.746234  0.756209  0.747918
DUK   0.162358  0.224440  0.746234  1.000000  0.752273  0.825406
NEE   0.232862  0.269408  0.756209  0.752273  1.000000  0.748668
SO    0.156748  0.224879  0.747918  0.825406  0.748668  1.000000
```

[9]:
```python
lowest_corr = []
for i in range(len(rets.corr())):
      lowest_corr.append(round(min(rets.corr().iloc[i]),4))
```

[10]:
```python
lowest_rets = rets.corr().idxmin(axis="columns").to_frame().reset_index()

lowest_rets.columns = ["Stock 1", "Stock 2"]

lowest_rets["Correlation"] = lowest_corr
```

[11]:
```python
lowest_rets.sort_values("Correlation")
```

[11]:

	Stock 1	Stock 2	Correlation
9	ELV	NEM	0.0269
6	NEM	ELV	0.0269
7	RGLD	ELV	0.0270
14	GOOG	NEM	0.0340
4	CDE	ELV	0.0352
13	AMZN	RGLD	0.0372
5	HL	ELV	0.0433
10	HCA	NEM	0.0483
11	UNH	NEM	0.0496
8	CVS	RGLD	0.0675
15	MSFT	RGLD	0.0925
12	AAPL	NEM	0.0935
19	SO	HCA	0.0948
17	DUK	AAPL	0.1015
0	COP	SO	0.1158
16	D	AAPL	0.1321
18	NEE	AAPL	0.1402
2	SHEL	SO	0.1703
3	XOM	RGLD	0.1950
1	CVX	RGLD	0.1984

[12]:
```python
# Expected annual return and volatility for any portfolio weights

def port_ret(weights, portfolio_df):
    port_rets = np.log(portfolio_df/portfolio_df.shift(1))
    return np.sum(port_rets.mean() * weights) * 252

def port_vol(weights, portfolio_df):
    port_rets = np.log(portfolio_df/portfolio_df.shift(1))
    return np.sqrt(np.dot(weights.T, np.dot(port_rets.cov() * 252, weights)))
```

[13]:
```python
# Optimal portfolio
import scipy.optimize as sco

noa = 5

def min_func_sharpe(weights, portfolio_df):
 return -port_ret(weights, portfolio_df) / port_vol(weights, portfolio_df)

# Equality constraint
cons = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1})

# Bounds for the parameters
bnds = tuple((0, 1) for x in range(noa))
```

```
# Starting parameter list
# Equal weights vector
eweights = np.array(noa * [1. / noa,])
```

[14]:
```
# Optimal portfolio by maximizing the Sharpe Ratio
# Solve for the optimal weights with the maximum sharpe ratio

train_port_sharpe_ratios = {}

for comb in portfolios:
    portfolio_df = TRAINING_df[comb]
    opts = sco.minimize(min_func_sharpe, eweights, args=(portfolio_df), method␣
 ↪= 'SLSQP',
                        bounds = bnds, constraints = cons)

    sharpe_ratio = -opts['fun']

    train_port_sharpe_ratios[tuple(comb)] = sharpe_ratio
```

[15]:
```
#Let's find the top 5 portfolios based on the sharpe ratio based on the␣
 ↪training data

train_top_5_SR = sorted(train_port_sharpe_ratios.values(), reverse= True)[:5]

train_top_5_portfolios = []

for i in range(0,5):
    train_top_5_portfolios.append(tuple(list(train_port_sharpe_ratios.
 ↪keys())[list(train_port_sharpe_ratios.values()).index(train_top_5_SR[i])]))
```

[16]:
```
for portfolio in train_top_5_portfolios:
    sharpe_ratio = train_port_sharpe_ratios[portfolio]
    print(str(portfolio) + " : " + str(sharpe_ratio))
```

```
('CVX', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.5337881380164358
('XOM', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.5337881341003818
('CVX', 'NEM', 'UNH', 'AMZN', 'NEE') : 1.5337881325288358
('XOM', 'NEM', 'UNH', 'AMZN', 'NEE') : 1.5337881320057958
('COP', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.533788129186189
```

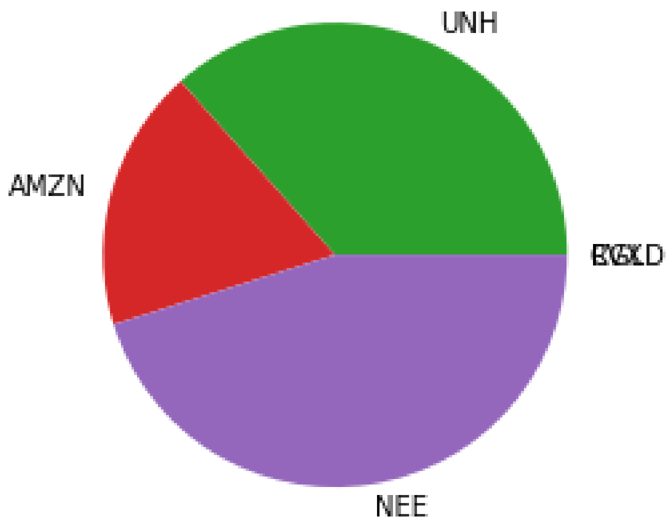
[17]:
```
train_port_weight_dict = {}


for portfolio in train_top_5_portfolios:

    portfolio_df = TRAINING_df[list(portfolio)]
```

```
    opts = sco.minimize(min_func_sharpe, eweights, args=(portfolio_df), method␣
↪= 'SLSQP',
                        bounds = bnds, constraints = cons)

    weights = opts['x']

    train_port_weight_dict[tuple(portfolio)] = weights

print(train_port_weight_dict)
```

```
{('CVX', 'RGLD', 'UNH', 'AMZN', 'NEE'): array([0.00000000e+00, 1.24812718e-16,
3.65775919e-01, 1.82600515e-01,
       4.51623566e-01]), ('XOM', 'RGLD', 'UNH', 'AMZN', 'NEE'):
array([0.00000000e+00, 1.51238493e-16, 3.65782399e-01, 1.82603882e-01,
       4.51613719e-01]), ('CVX', 'NEM', 'UNH', 'AMZN', 'NEE'):
array([3.15844287e-16, 0.00000000e+00, 3.65783202e-01, 1.82606949e-01,
       4.51609849e-01]), ('XOM', 'NEM', 'UNH', 'AMZN', 'NEE'):
array([9.45011536e-17, 1.15057492e-16, 3.65783709e-01, 1.82607677e-01,
       4.51608614e-01]), ('COP', 'RGLD', 'UNH', 'AMZN', 'NEE'):
array([2.42628924e-16, 0.00000000e+00, 3.65794626e-01, 1.82602419e-01,
       4.51602955e-01])}
```

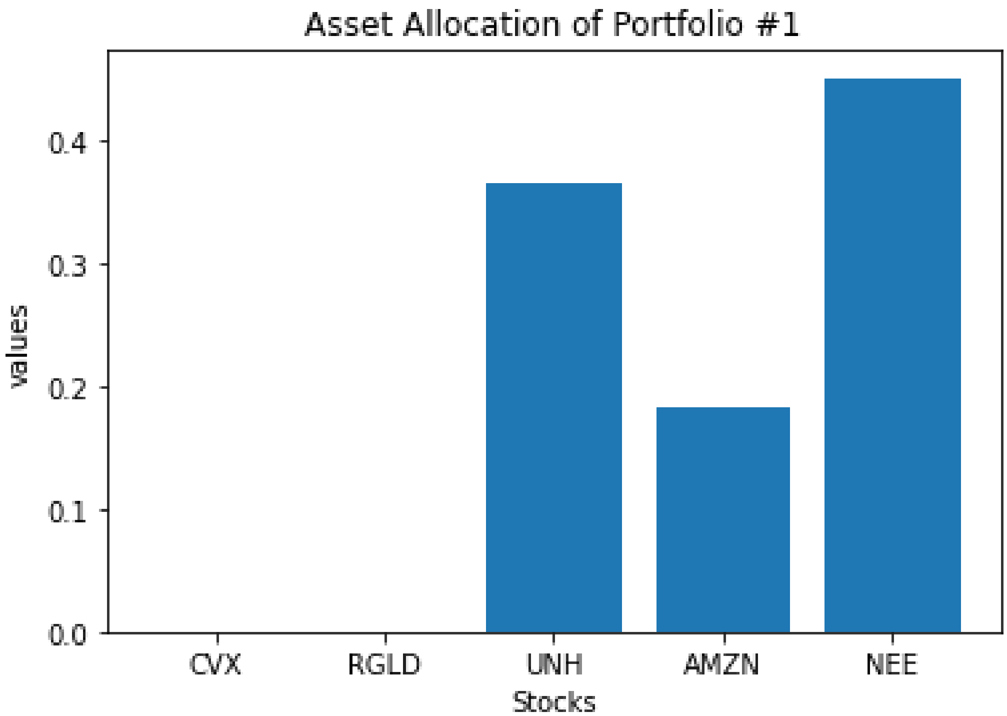
[18]:
```
#Let's take a look at the distribution of the portfolio with the highest sharpe␣
↪ratio in the training dataset
plt.pie(train_port_weight_dict[train_top_5_portfolios[0]], labels =␣
↪train_top_5_portfolios[0])
```

[18]:
```
([<matplotlib.patches.Wedge at 0x7efcd016ca20>,
  <matplotlib.patches.Wedge at 0x7efcd016cf60>,
  <matplotlib.patches.Wedge at 0x7efcd01804a8>,
  <matplotlib.patches.Wedge at 0x7efcd01809b0>,
  <matplotlib.patches.Wedge at 0x7efcd0180eb8>],
 [Text(1.1, 0.0, 'CVX'),
  Text(1.1, 4.313217742831226e-16, 'RGLD'),
  Text(0.4502206491601833, 1.0036440440065308, 'UNH'),
  Text(-1.060236434230373, 0.293084806038226, 'AMZN'),
  Text(0.16653405429284399, -1.0873207478756157, 'NEE')])
```



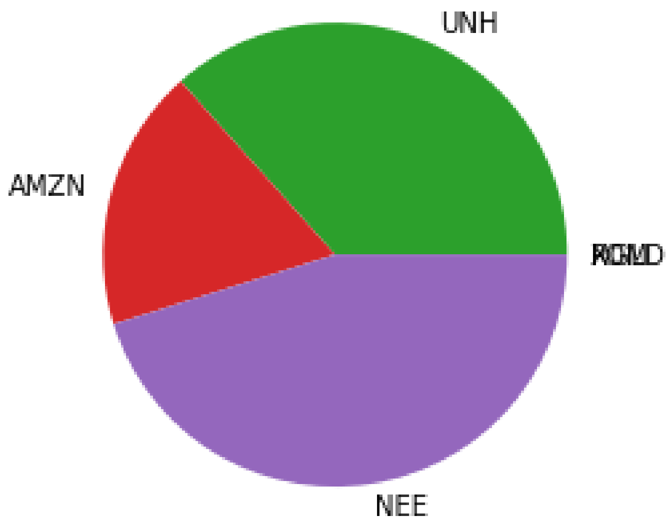

```
[19]: plt.bar(list(train_top_5_portfolios[0]),␣
       ↪train_port_weight_dict[train_top_5_portfolios[0]])
      plt.title('Asset Allocation of Portfolio #1')
      plt.xlabel("Stocks")
      plt.ylabel('values')
```

```
[19]: Text(0, 0.5, 'values')
```



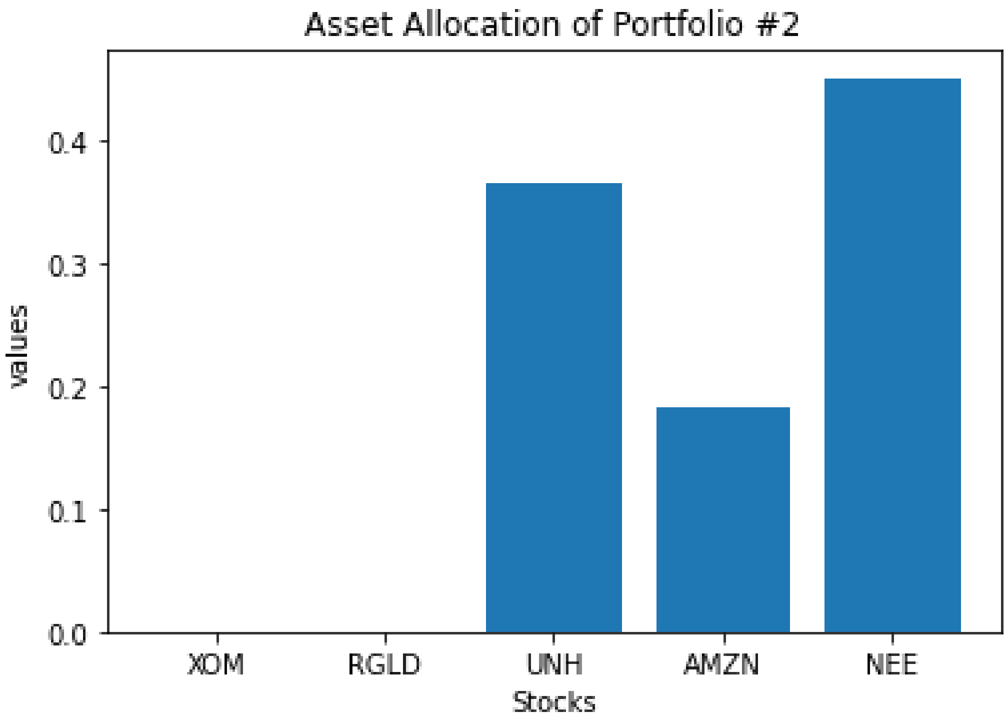
[20]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[1]], labels =␣
↪train_top_5_portfolios[1])
```

[20]:
```
([<matplotlib.patches.Wedge at 0x7efccfc80d30>,
  <matplotlib.patches.Wedge at 0x7efccfc0c2b0>,
  <matplotlib.patches.Wedge at 0x7efccfc0c7b8>,
  <matplotlib.patches.Wedge at 0x7efccfc0ccc0>,
  <matplotlib.patches.Wedge at 0x7efccfc14208>],
 [Text(1.1, 0.0, 'XOM'),
  Text(1.1, 5.226426920872151e-16, 'RGLD'),
  Text(0.450200164056118, 1.0036532330859322, 'UNH'),
  Text(-1.0602514977081412, 0.2930303083430853, 'AMZN'),
  Text(0.1665678525811384, -1.087315570791897, 'NEE')])
```



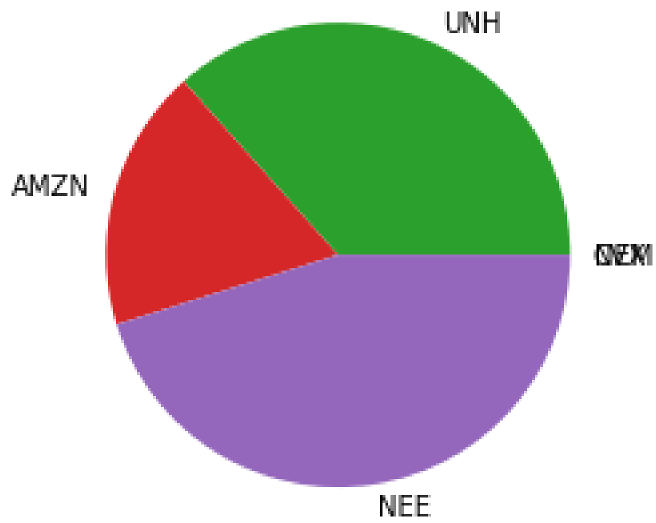

```
[21]: plt.bar(list(train_top_5_portfolios[1]),␣
       ↪train_port_weight_dict[train_top_5_portfolios[1]])
      plt.title('Asset Allocation of Portfolio #2')
      plt.xlabel("Stocks")
      plt.ylabel('values')
```

```
[21]: Text(0, 0.5, 'values')
```



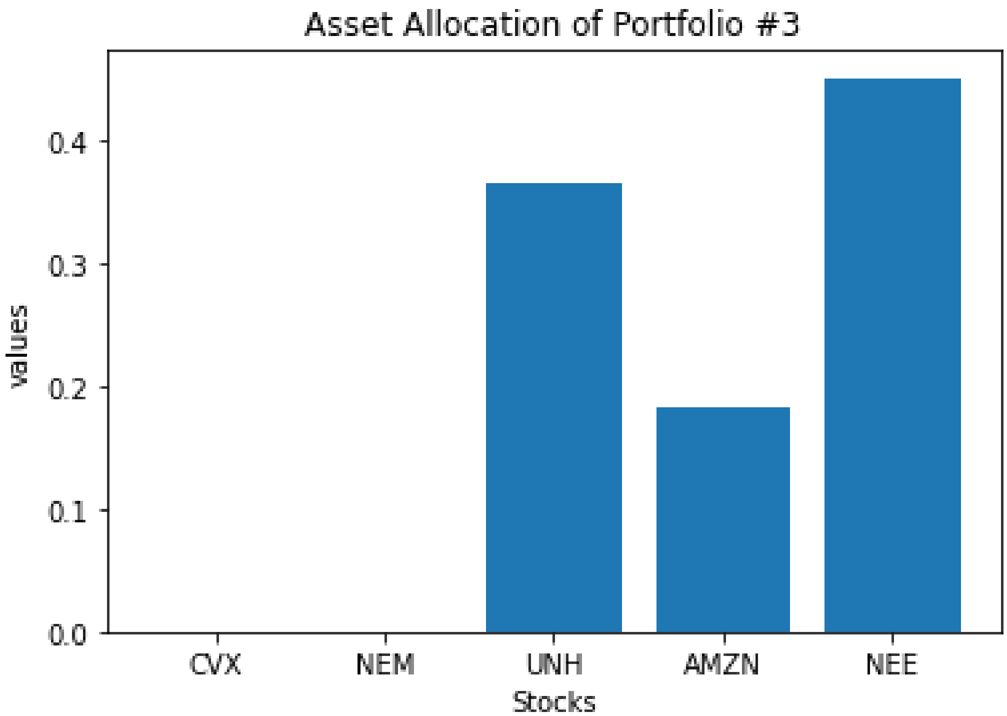
[22]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[2]], labels =
↪train_top_5_portfolios[2])
```

[22]:
```
([<matplotlib.patches.Wedge at 0x7efccfbaeeb8>,
  <matplotlib.patches.Wedge at 0x7efccfbb9438>,
  <matplotlib.patches.Wedge at 0x7efccfbb9940>,
  <matplotlib.patches.Wedge at 0x7efccfbb9e10>,
  <matplotlib.patches.Wedge at 0x7efccfbc2358>],
 [Text(1.1, 1.0914795193780262e-15, 'CVX'),
  Text(1.1, 2.1829590387560524e-15, 'NEM'),
  Text(0.4501976268971476, 1.0036543711538235, 'UNH'),
  Text(-1.0602558049635622, 0.2930147232496498, 'AMZN'),
  Text(0.1665810868068073, -1.0873135433343333, 'NEE')])
```



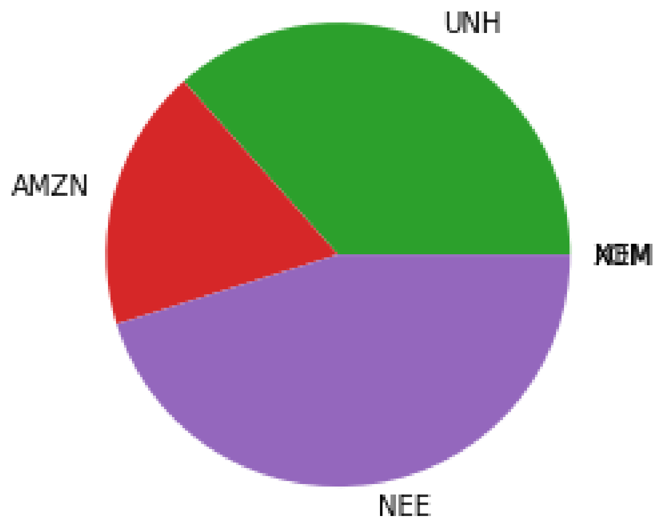
[23]:
```
plt.bar(list(train_top_5_portfolios[2]),␣
 ↪train_port_weight_dict[train_top_5_portfolios[2]])
plt.title('Asset Allocation of Portfolio #3')
plt.xlabel("Stocks")
plt.ylabel('values')
```

[23]: Text(0, 0.5, 'values')



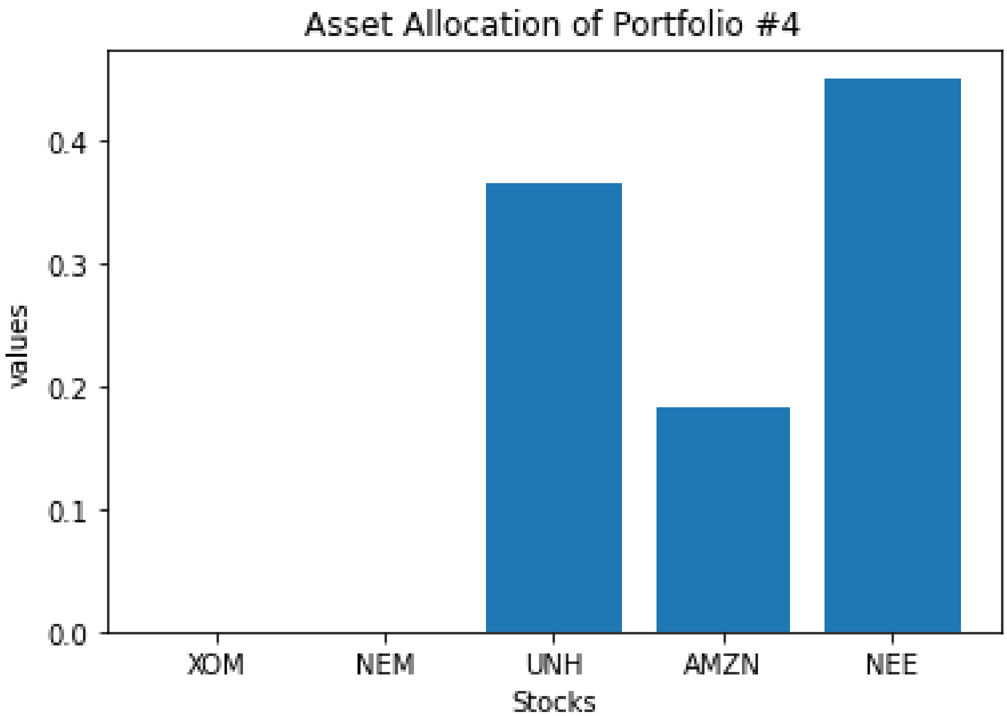
[24]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[3]], labels =␣
↪train_top_5_portfolios[3])
```

[24]:
```
([<matplotlib.patches.Wedge at 0x7efcd018a860>,
  <matplotlib.patches.Wedge at 0x7efccfbfd898>,
  <matplotlib.patches.Wedge at 0x7efccfbfda58>,
  <matplotlib.patches.Wedge at 0x7efccfbe3a20>,
  <matplotlib.patches.Wedge at 0x7efccfc09be0>],
 [Text(1.1, 3.2657255269966783e-16, 'XOM'),
  Text(1.1, 1.0507552403927833e-15, 'NEM'),
  Text(0.45019602942521003, 1.0036550877117973, 'UNH'),
  Text(-1.0602574098377298, 0.2930089160489634, 'AMZN'),
  Text(0.16658536247443897, -1.087312888275155, 'NEE')])
```



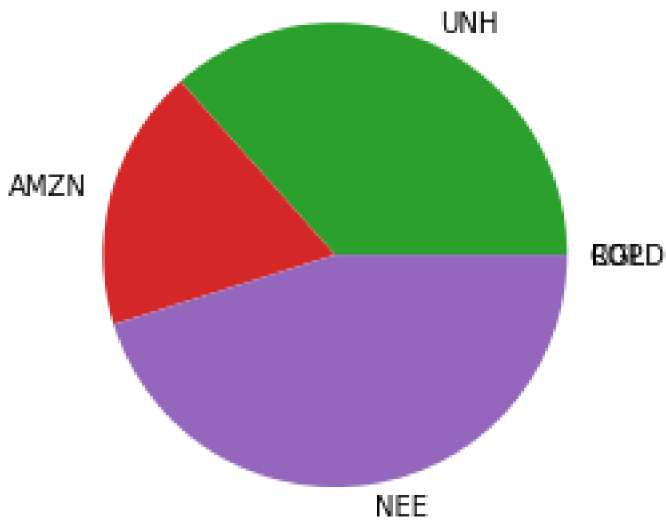

```
[25]: plt.bar(list(train_top_5_portfolios[3]),
       ↪train_port_weight_dict[train_top_5_portfolios[3]])
      plt.title('Asset Allocation of Portfolio #4')
      plt.xlabel("Stocks")
      plt.ylabel('values')
```

```
[25]: Text(0, 0.5, 'values')
```



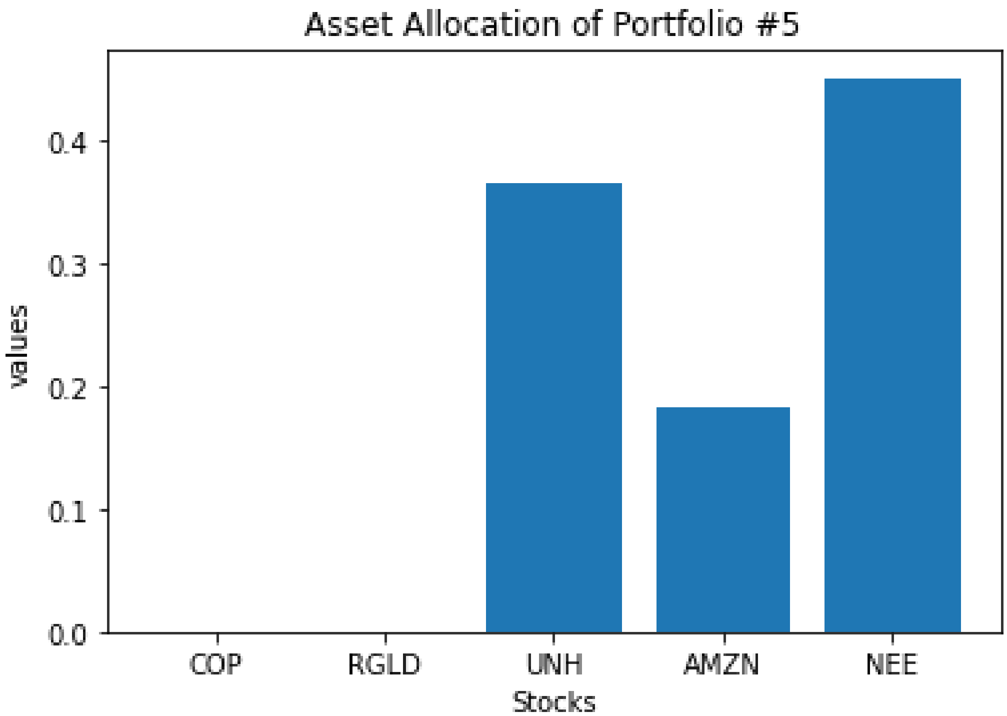
[26]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[4]], labels =␣
↪train_top_5_portfolios[4])
```

[26]:
```
([<matplotlib.patches.Wedge at 0x7efccfa6bf98>,
  <matplotlib.patches.Wedge at 0x7efccfa774a8>,
  <matplotlib.patches.Wedge at 0x7efccfa779b0>,
  <matplotlib.patches.Wedge at 0x7efccfa77eb8>,
  <matplotlib.patches.Wedge at 0x7efccfa863c8>],
 [Text(1.1, 8.384654074125996e-16, 'COP'),
  Text(1.1, 1.6769308148251991e-15, 'RGLD'),
  Text(0.4501616365174784, 1.0036705141668285, 'UNH'),
  Text(-1.0602726476988642, 0.2929537720215265, 'AMZN'),
  Text(0.1660460294691046, -1.0873099403007878, 'NEE')])
```



[27]:
```
plt.bar(list(train_top_5_portfolios[4]), train_port_weight_dict[train_top_5_portfolios[4]])
plt.title('Asset Allocation of Portfolio #5')
plt.xlabel("Stocks")
plt.ylabel('values')
```

[27]:
```
Text(0, 0.5, 'values')
```



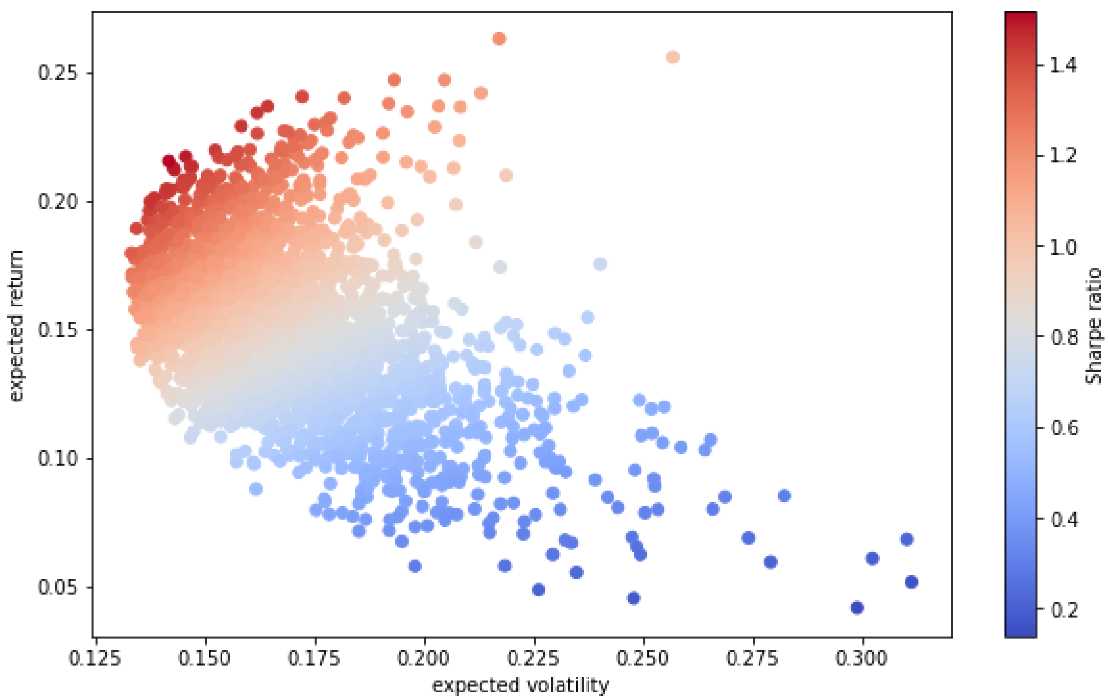
[28]:
```
#Since all the portfolio's are very similar let's focus on the one with the
↪highest sharpe ratio and see how it's distributed

top_port = train_top_5_portfolios[0]
```

[29]:
```
weights = train_port_weight_dict[top_port]
portfolio_df = TRAINING_df[list(top_port)]
TRAINING_port_ret = port_ret(weights, portfolio_df)
TRAINING_port_vol = port_vol(weights, portfolio_df)
print("Portfolio Returns: " + str(TRAINING_port_ret))
print("Portfolio Volatility: " + str(TRAINING_port_vol))
```

```
Portfolio Returns: 0.21995643529715317
Portfolio Volatility: 0.1434073128128444
```

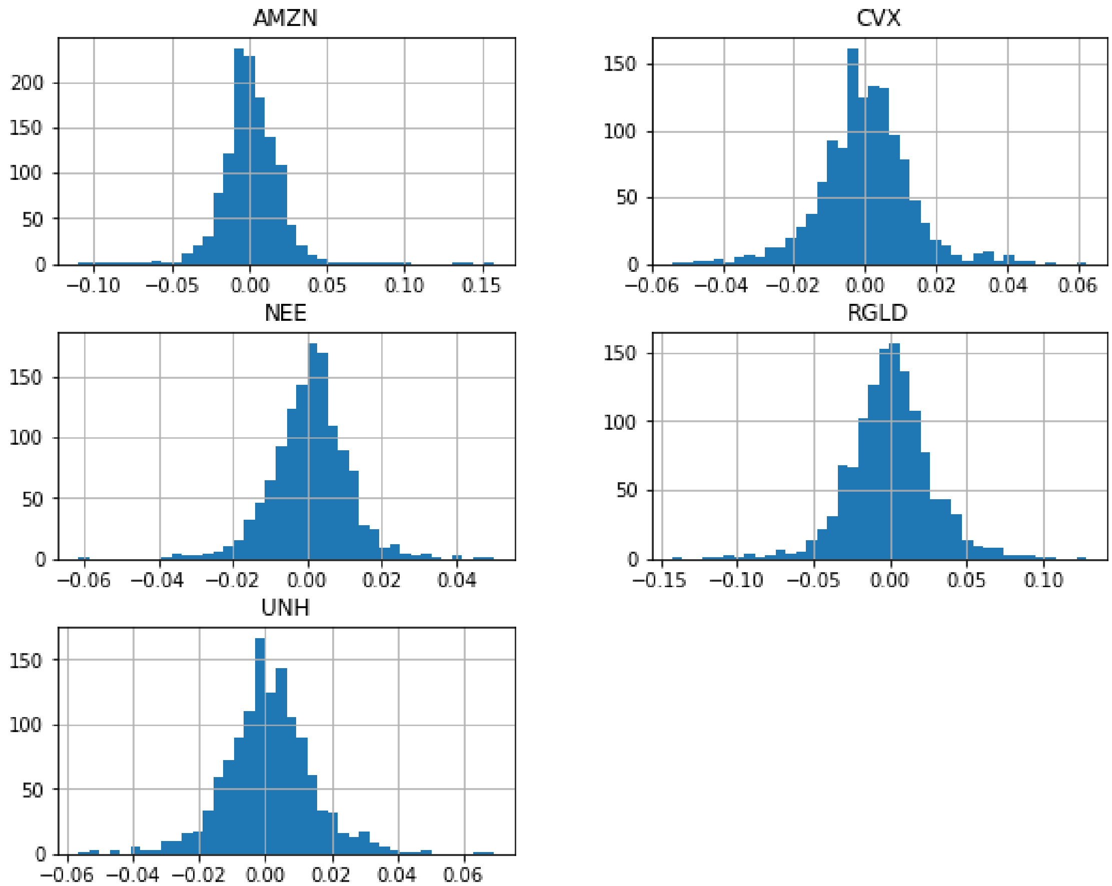
[30]:
```
#Lets take a closer look at the portfolio with the highest possible sharpe
↪ratio using Monte Carlo Simulation

def monte_carlo_sim(portfolio):

    prets = []
    pvols = []
```

```
    portfolio_df = TRAINING_df[list(portfolio)]

    # Monte Carlo simulation of portfolio weights
    for p in range (2500):
        weights = np.random.random(noa)
        weights /= np.sum(weights)
        # Collect the resulting returns and volatility in list objects
        prets.append(port_ret(weights, portfolio_df))
        pvols.append(port_vol(weights, portfolio_df))

    prets = np.array(prets)
    pvols = np.array(pvols)

    plt.figure(figsize = (10,6))
    plt.scatter(pvols, prets, c = prets/pvols, marker = 'o', cmap = 'coolwarm')
    plt.xlabel('expected volatility')
    plt.ylabel('expected return')
    plt.colorbar(label = 'Sharpe ratio');


monte_carlo_sim(top_port)
```



[31]:
```
#Examine the distribution of returns for each stock in the optimal portfolio
port_rets = rets[list(top_port)]
```

```
port_rets.hist(bins = 40, figsize = (10, 8));
```



0.0.2 Now let's see how the portfolio's with highest sharpe ratios performed in the PRE-COVID testing dataset

[32]:
```
#Let's take a quick look at the returns in the PRE-COVID testing dataset

PRECOVID_rets = PRECOVID_TESTING_df.pct_change().dropna()
PRECOVID_rets.head(10)
```

[32]:
```
                 COP       CVX      SHEL       XOM       CDE        HL  \
Date
2017-01-04  0.009287 -0.000254  0.010141 -0.011002  0.018481  0.012727
2017-01-05 -0.002937 -0.004329  0.008785 -0.014907  0.133064  0.046679
2017-01-06 -0.003731 -0.004006 -0.008530 -0.000565 -0.063167 -0.027444
2017-01-09 -0.021285 -0.008559 -0.021330 -0.016497  0.004748 -0.001764
2017-01-10  0.000000 -0.007597 -0.004213 -0.012753  0.036862  0.028269
2017-01-11  0.031413  0.008438  0.020232  0.010241 -0.000912 -0.005155
```

```
2017-01-12 -0.020890  0.001984  0.004327 -0.005414 -0.006387  0.003454
2017-01-13  0.008774  0.001894 -0.004129  0.000116  0.045914  0.027539
2017-01-17 -0.008697 -0.000859  0.001082  0.011697  0.018437  0.020101
2017-01-18  0.002393 -0.002924 -0.012604 -0.012363 -0.011207 -0.004926

                 NEM      RGLD       CVS       ELV       HCA       UNH  \
Date
2017-01-04  0.009529  0.008852 -0.007468 -0.001326  0.035858  0.002849
2017-01-05  0.046053  0.033713  0.020941  0.010626 -0.004149  0.001668
2017-01-06 -0.031447 -0.024423  0.009580 -0.001522 -0.002473  0.001418
2017-01-09 -0.001694  0.005190 -0.006083 -0.010807  0.030018 -0.002833
2017-01-10 -0.007919  0.017312  0.011873  0.024862 -0.008236 -0.002284
2017-01-11 -0.020240 -0.004777  0.001210 -0.003485  0.013287  0.001919
2017-01-12  0.002910 -0.001500 -0.002054  0.016183 -0.002396  0.002903
2017-01-13  0.001740  0.009163 -0.007506  0.002294  0.003539 -0.003449
2017-01-17  0.017666  0.017862  0.023664 -0.011984  0.019270 -0.007046
2017-01-18  0.003415 -0.003802 -0.004528  0.003202 -0.014828 -0.018175

                AAPL      AMZN      GOOG      MSFT         D       DUK  \
Date
2017-01-04 -0.001119  0.004657  0.000967 -0.004474 -0.000918 -0.001029
2017-01-05  0.005086  0.030732  0.009048  0.000000  0.001313  0.001288
2017-01-06  0.011148  0.019912  0.015277  0.008668  0.008128 -0.003344
2017-01-09  0.009159  0.001168  0.000620 -0.003183 -0.015345 -0.010969
2017-01-10  0.001009 -0.001280 -0.002306 -0.000319 -0.003830 -0.001827
2017-01-11  0.005373  0.003920  0.003877  0.009103  0.002651  0.007843
2017-01-12 -0.004175  0.018297 -0.001919 -0.009179 -0.004628  0.005707
2017-01-13 -0.001761  0.004302  0.001885  0.001438 -0.000930 -0.004256
2017-01-17  0.008065 -0.009080 -0.004048 -0.002711  0.013163  0.003238
2017-01-18 -0.000083 -0.002766  0.001815 -0.000480 -0.000394  0.000516

                 NEE        SO
Date
2017-01-04  0.002948 -0.001019
2017-01-05 -0.000588  0.003062
2017-01-06 -0.002941 -0.002645
2017-01-09 -0.002529 -0.009794
2017-01-10  0.001943 -0.003091
2017-01-11  0.007000  0.007441
2017-01-12  0.000754  0.005334
2017-01-13 -0.003765 -0.004082
2017-01-17  0.009828  0.018238
2017-01-18 -0.001580 -0.001408
```

[33]:
```
#Now let's take a look at how the top portfolios found using the training
↪dataset performed in the PRE-COVID testing dataset
```

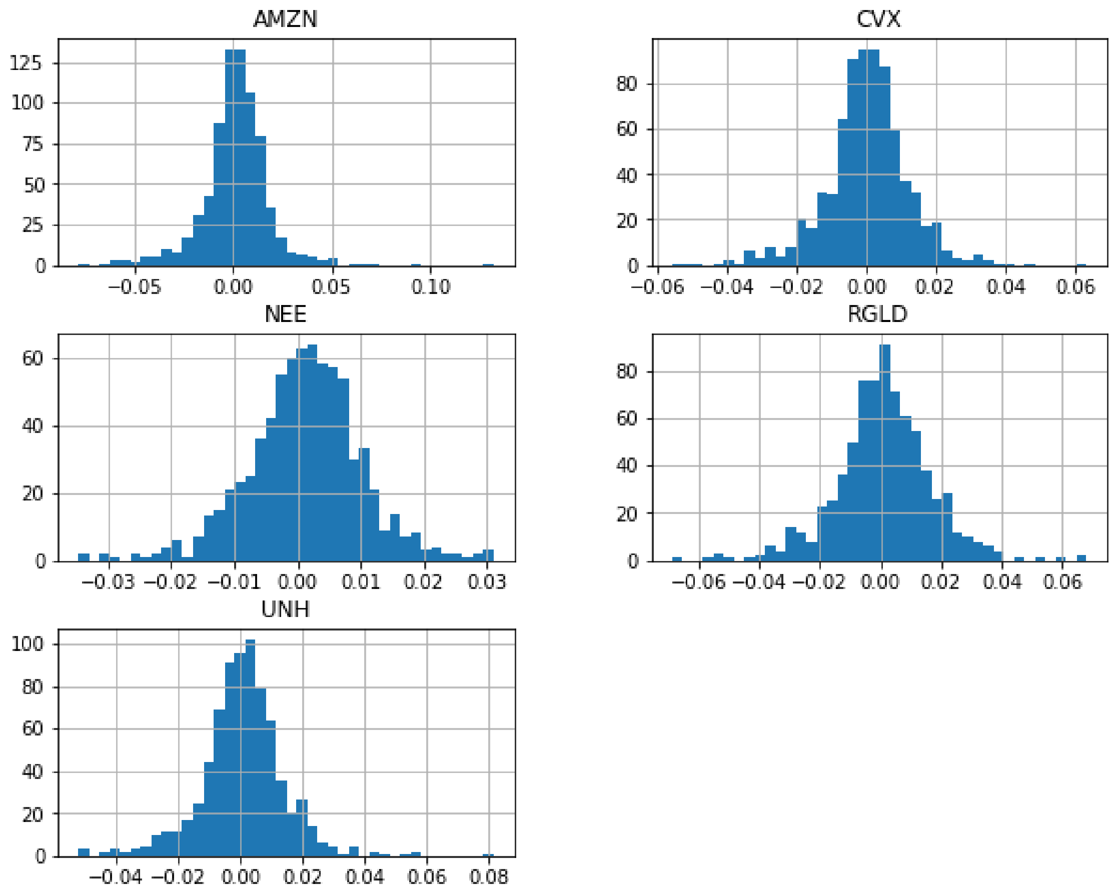
```
for portfolio in train_top_5_portfolios:

    weights = train_port_weight_dict[portfolio]
    portfolio_df = PRECOVID_TESTING_df[list(portfolio)]
    sharpe_ratio = -min_func_sharpe(weights, portfolio_df)

    print(str(portfolio) + " : " + str(sharpe_ratio))
```

```
('CVX', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.9213678647677745
('XOM', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.9213542282791605
('CVX', 'NEM', 'UNH', 'AMZN', 'NEE') : 1.9213498929782922
('XOM', 'NEM', 'UNH', 'AMZN', 'NEE') : 1.9213483607528457
('COP', 'RGLD', 'UNH', 'AMZN', 'NEE') : 1.9213363061797535
```

[34]:
```
#Now let's take a look closer at how the top portfolio in the training dataset␣
↪performed

weights = train_port_weight_dict[top_port]
portfolio_df = PRECOVID_TESTING_df[list(top_port)]
PRECOVID_port_ret = port_ret(weights, portfolio_df)
PRECOVID_port_vol = port_vol(weights, portfolio_df)
print("Portfolio Returns: " + str(PRECOVID_port_ret))
print("Portfolio Volatility: " + str(PRECOVID_port_vol))
```

```
Portfolio Returns: 0.2532479060348971
Portfolio Volatility: 0.13180604853381672
```

[35]:
```
port_rets = PRECOVID_rets[list(top_port)]
port_rets.hist(bins = 40, figsize = (10, 8));
```



0.0.3 Now let's look at the portfolio's with highest sharpe ratios in the COVID testing dataset

[36]:
```python
#Let's take a quick look at the returns in the COVID testing dataset

COVID_rets = COVID_TESTING_df.pct_change().dropna()
COVID_rets.head(10)
```

[36]:
```
                 COP       CVX      SHEL       XOM       CDE        HL  \
Date
2020-01-03  0.003666 -0.003459  0.007867 -0.008040 -0.014085 -0.020468
2020-01-06  0.011872 -0.003388  0.012456  0.007678 -0.100000 -0.011940
2020-01-07  0.000000 -0.012770 -0.009186 -0.008184 -0.005772  0.030211
2020-01-08 -0.023165 -0.011423 -0.011755 -0.015080 -0.087083 -0.043988
2020-01-09  0.017400 -0.001614 -0.000168  0.007656  0.017488 -0.058282
2020-01-10 -0.009838 -0.009106 -0.011227 -0.008888  0.023438  0.003257
2020-01-13 -0.004433  0.001889 -0.000847  0.009546 -0.018321 -0.009740
2020-01-14  0.000154 -0.003086 -0.000678 -0.008596  0.024883  0.029508
2020-01-15 -0.002149 -0.001462 -0.001697 -0.001590  0.056146  0.031847
```

```
2020-01-16  0.001077  0.006544 -0.000850 -0.003908  0.010057 -0.003086

                 NEM      RGLD       CVS       ELV       HCA       UNH  \
Date
2020-01-03 -0.009024 -0.008174 -0.007956 -0.013261  0.003051 -0.010120
2020-01-06  0.010040 -0.010988  0.003942  0.012025  0.003785  0.006942
2020-01-07 -0.000694  0.011531 -0.003791 -0.003029 -0.001347 -0.006037
2020-01-08 -0.026602 -0.071393 -0.012503  0.026507  0.006608  0.021084
2020-01-09 -0.009981  0.005287  0.002752 -0.003480 -0.012460 -0.005678
2020-01-10  0.014642  0.014262 -0.010294  0.004341  0.004884  0.003093
2020-01-13  0.004258 -0.022937  0.009014 -0.035745 -0.006615 -0.031444
2020-01-14  0.008952  0.010703  0.014706  0.000472  0.005096  0.008361
2020-01-15  0.016110  0.019845  0.019504  0.015730 -0.004462  0.028345
2020-01-16  0.006893  0.003229  0.010363  0.011606  0.003532  0.014608

                AAPL      AMZN      GOOG      MSFT         D       DUK  \
Date
2020-01-03 -0.009722 -0.012139 -0.004907 -0.012452 -0.002440  0.000664
2020-01-06  0.007969  0.014886  0.024657  0.002585  0.007706  0.004867
2020-01-07 -0.004703  0.002092 -0.000624 -0.009118 -0.002185 -0.006275
2020-01-08  0.016086 -0.007809  0.007880  0.015929 -0.006325  0.001440
2020-01-09  0.021241  0.004799  0.011044  0.012493  0.002816  0.002434
2020-01-10  0.002261 -0.009411  0.006973 -0.004627  0.001831 -0.001986
2020-01-13  0.021364  0.004323  0.006645  0.012025 -0.000244  0.008845
2020-01-14 -0.013503 -0.011558 -0.005802 -0.007043 -0.001219  0.000658
2020-01-15 -0.004285 -0.003969  0.005815  0.006476  0.012691  0.013034
2020-01-16  0.012526  0.008550  0.008685  0.018323  0.006266  0.007460

                 NEE        SO
Date
2020-01-03  0.007124 -0.000958
2020-01-06  0.004993  0.003996
2020-01-07 -0.000870 -0.003025
2020-01-08 -0.000456 -0.000320
2020-01-09  0.007836  0.010543
2020-01-10  0.001892  0.006323
2020-01-13  0.011702  0.013823
2020-01-14  0.005398  0.005888
2020-01-15  0.015541  0.010166
2020-01-16  0.002743  0.008692
```

[37]:

```
#Now let's take a look at how the top portfolios found using the training␣
↪dataset performed in the COVID testing dataset

for portfolio in train_top_5_portfolios:

    weights = train_port_weight_dict[portfolio]
```

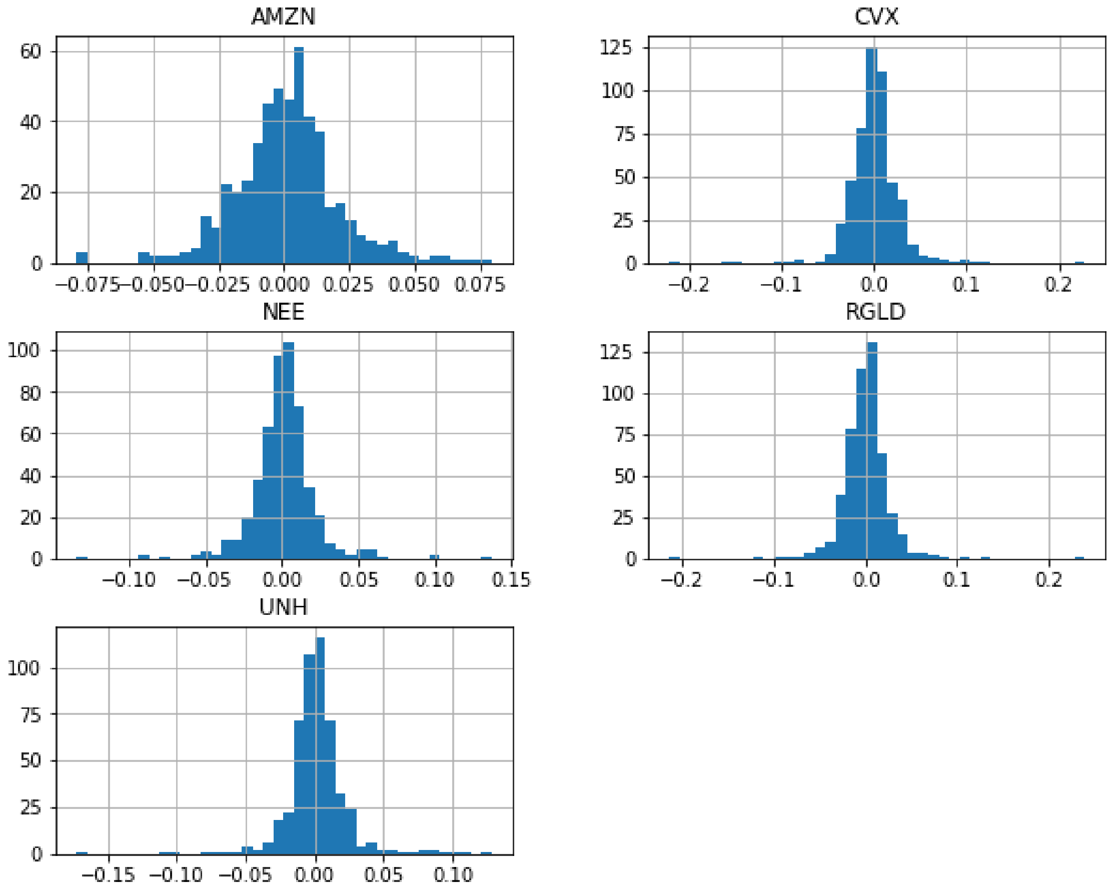
```
    portfolio_df = COVID_TESTING_df[list(portfolio)]
    sharpe_ratio = -min_func_sharpe(weights, portfolio_df)

    print(str(portfolio) + " : " + str(sharpe_ratio))
```

```
('CVX', 'RGLD', 'UNH', 'AMZN', 'NEE') : 0.9443305643406732
('XOM', 'RGLD', 'UNH', 'AMZN', 'NEE') : 0.944332667943389
('CVX', 'NEM', 'UNH', 'AMZN', 'NEE') : 0.9443342184146928
('XOM', 'NEM', 'UNH', 'AMZN', 'NEE') : 0.9443346091872103
('COP', 'RGLD', 'UNH', 'AMZN', 'NEE') : 0.9443328310190686
```

[38]:
```
#Now let's take a look closer at how the top portfolio in the training dataset␣
 ↪performed

weights = train_port_weight_dict[top_port]
portfolio_df = COVID_TESTING_df[list(top_port)]
COVID_port_ret = port_ret(weights, portfolio_df)
COVID_port_vol = port_vol(weights, portfolio_df)
print("Portfolio Returns: " + str(COVID_port_ret))
print("Portfolio Volatility: " + str(COVID_port_vol))
```

```
Portfolio Returns: 0.26596690882167395
Portfolio Volatility: 0.28164598167737026
```

[39]:
```
port_rets = COVID_rets[list(top_port)]
port_rets.hist(bins = 40, figsize = (10, 8));
```


AMZN
0
20
40
60
−0.075
−0.050
−0.025
0.000
0.025
0.050
0.075
CVX
0
25
50
75
100
125
−0.2
−0.1
0.0
0.1
0.2
NEE
0
20
40
60
80
100
−0.10
−0.05
0.00
0.05
0.10
0.15
RGLD
0
25
50
75
100
125
−0.2
−0.1
0.0
0.1
0.2
UNH
0
25
50
75
100
−0.15
−0.10
−0.05
0.00
0.05
0.10