K-Means Clustering Method

August 31, 2022

[1]:
```
#Data import

import pandas as pd
import numpy as np
import math
from sklearn.cluster import KMeans
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 datas sets

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']

TRAINING_MARKET_df = pd.DataFrame(SPY_df['Close']).loc['2012-01-01':
↪'2016-12-31']
```

[3]:
```
TRAINING_df.columns
```

[3]:
```
Index(['COP', 'CVX', 'SHEL', 'XOM', 'CDE', 'HL', 'NEM', 'RGLD', 'CVS', 'ELV',
       'HCA', 'UNH', 'AAPL', 'AMZN', 'GOOG', 'MSFT', 'D', 'DUK', 'NEE', 'SO'],
      dtype='object')
```

0.0.1 First let's create a portfolio using the training data

[4]:
```
#Calculate the annual mean returns and variances

daily_returns = TRAINING_df.pct_change().dropna()
annual_mean_returns = daily_returns.mean() * 252
annual_return_variance = daily_returns.var() * 252
```

```
market_returns = TRAINING_MARKET_df.pct_change().dropna()
```

[5]:
```
TRAINING_df2 = pd.DataFrame(TRAINING_df.columns, columns=['Ticker'])
TRAINING_df2['Annual Returns'] = annual_mean_returns.values
TRAINING_df2['Annual Variances'] = annual_return_variance.values
```

[6]:
```
betas = np.array([])
for i in TRAINING_df2.index:
    symbol = TRAINING_df2['Ticker'][i]
    rets = np.array(daily_returns[symbol])
    mkt_rets = np.array(market_returns['Close'])
    mkt_cov = np.cov(rets, mkt_rets)[0][1]
    mkt_var = mkt_rets.var()
    beta = np.array([mkt_cov/mkt_var])
    betas = np.concatenate((betas, beta))

TRAINING_df2['Betas'] = betas
```

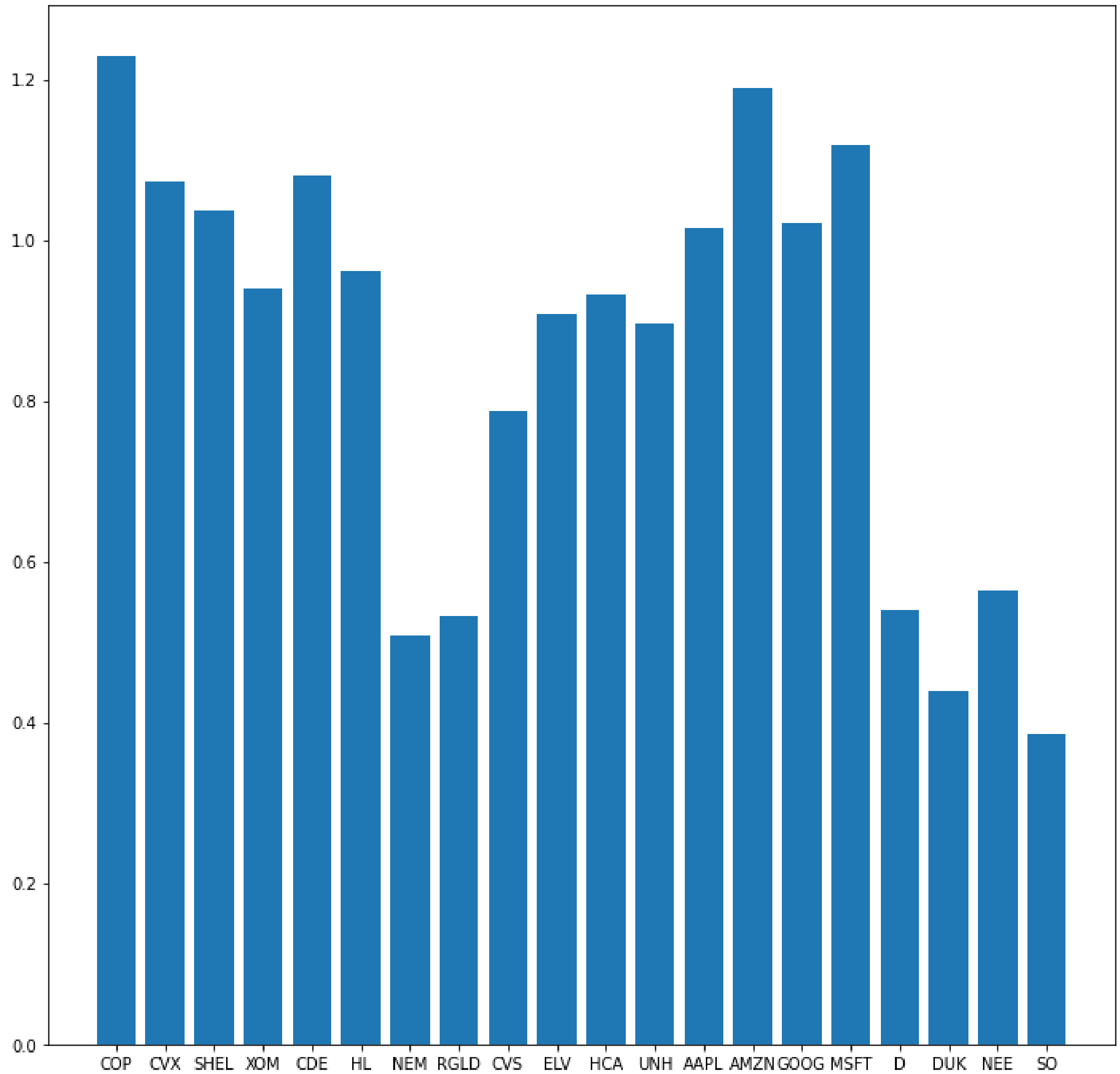
[7]:
```
TRAINING_df2
```

[7]:

	Ticker	Annual Returns	Annual Variances	Betas
0	COP	0.053882	0.076181	1.229764
1	CVX	0.071782	0.042252	1.071533
2	SHEL	0.021782	0.050823	1.037784
3	XOM	0.054754	0.030664	0.939941
4	CDE	-0.002884	0.406178	1.081356
5	HL	0.141216	0.307043	0.961650
6	NEM	-0.021780	0.163213	0.508015
7	RGLD	0.089522	0.188381	0.531687
8	CVS	0.160351	0.032281	0.786785
9	ELV	0.198703	0.058139	0.907745
10	HCA	0.333212	0.084755	0.932622
11	UNH	0.265784	0.044584	0.896916
12	AAPL	0.188954	0.068087	1.015140
13	AMZN	0.334733	0.095812	1.189581
14	GOOG	0.196299	0.054359	1.020132
15	MSFT	0.223789	0.054272	1.118661
16	D	0.125428	0.023711	0.540739
17	DUK	0.091736	0.023503	0.439980
18	NEE	0.186661	0.025655	0.562953
19	SO	0.073070	0.019811	0.385934

[8]:
```
plt.figure(figsize=(12,12))
plt.bar(TRAINING_df2['Ticker'].values, TRAINING_df2['Betas'].values)
```

[8]:
```
<BarContainer object of 20 artists>
```

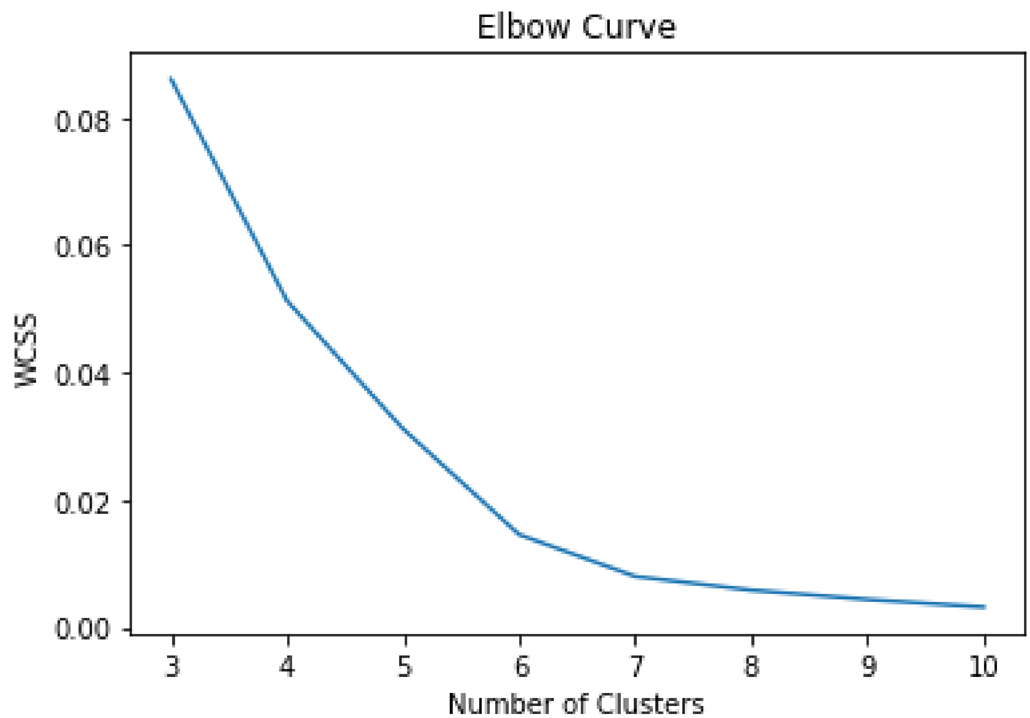


[9]:

```python
#Use the Elbow method to determine the number of clusters to use to group the stocks based on the beta values
#Note the "intertia" is the Within-cluster Sum of Squares (WCSS)

X = TRAINING_df2['Betas'].values.reshape(-1, 1)

inertia_list = []
for k in range(3,11):
    #Create and train the model
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(X)
    inertia_list.append(kmeans.inertia_)

#Plot the data
```

```
plt.plot(range(3,11), inertia_list)
plt.title('Elbow Curve')
plt.xlabel('Number of Clusters')
plt.xticks(range(3,11))
plt.ylabel('WCSS')
```

[9]: Text(0, 0.5, 'WCSS')



[10]:
```
#From the elbow method we see that the optimum number of clusters is 7 as this
↪is the point of diminishing returns
#We now get the cluster labels / group for each stock

kmeans = KMeans(n_clusters=7).fit(X)
labels = kmeans.labels_
```

[11]:
```
TRAINING_df2['Group'] = labels
```

[12]:
```
TRAINING_df2
```

[12]:

	Ticker	Annual Returns	Annual Variances	Betas	Group
0	COP	0.053882	0.076181	1.229764	4
1	CVX	0.071782	0.042252	1.071533	0
2	SHEL	0.021782	0.050823	1.037784	6

```
3     XOM        0.054754          0.030664  0.939941      2
4     CDE       -0.002884          0.406178  1.081356      0
5      HL        0.141216          0.307043  0.961650      2
6     NEM       -0.021780          0.163213  0.508015      3
7    RGLD        0.089522          0.188381  0.531687      3
8     CVS        0.160351          0.032281  0.786785      5
9     ELV        0.198703          0.058139  0.907745      2
10    HCA        0.333212          0.084755  0.932622      2
11    UNH        0.265784          0.044584  0.896916      2
12   AAPL        0.188954          0.068087  1.015140      6
13   AMZN        0.334733          0.095812  1.189581      4
14   GOOG        0.196299          0.054359  1.020132      6
15   MSFT        0.223789          0.054272  1.118661      0
16      D        0.125428          0.023711  0.540739      3
17    DUK        0.091736          0.023503  0.439980      1
18    NEE        0.186661          0.025655  0.562953      3
19     SO        0.073070          0.019811  0.385934      1
```

[13]:
```python
cluster_dict = {}
for i in TRAINING_df2.index:
    cluster_label = TRAINING_df2['Group'][i]
    ticker = TRAINING_df2['Ticker'][i]
    if cluster_label not in cluster_dict:
        cluster_dict[cluster_label] = set([ticker])
    else:
        cluster_dict[cluster_label].add(ticker)

cluster_dict
```

[13]:
```
{4: {'AMZN', 'COP'},
 0: {'CDE', 'CVX', 'MSFT'},
 6: {'AAPL', 'GOOG', 'SHEL'},
 2: {'ELV', 'HCA', 'HL', 'UNH', 'XOM'},
 3: {'D', 'NEE', 'NEM', 'RGLD'},
 5: {'CVS'},
 1: {'DUK', 'SO'}}
```

[14]:
```python
# Create all possible combinations of a portfolio of 8 stocks and select the␣
↪portolfios that include exactly one stock from each cluster

from itertools import combinations

all_tickers = list(TRAINING_df2['Ticker'])

combs = list(combinations(all_tickers, 7))

#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)

    cluster_count = 0

    for cluster in cluster_dict:

        if len(set.intersection(comb_set, cluster_dict[cluster])) == 1:
            cluster_count += 1
        else:
            break

    if cluster_count == 7:
        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
len(portfolios)
```

[14]: 720

[15]:
```
portfolios[:10]
```

[15]:
```
[['COP', 'CVX', 'SHEL', 'XOM', 'NEM', 'CVS', 'DUK'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'NEM', 'CVS', 'SO'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'RGLD', 'CVS', 'DUK'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'RGLD', 'CVS', 'SO'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'CVS', 'D', 'DUK'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'CVS', 'D', 'SO'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'CVS', 'DUK', 'NEE'],
 ['COP', 'CVX', 'SHEL', 'XOM', 'CVS', 'NEE', 'SO'],
 ['COP', 'CVX', 'SHEL', 'HL', 'NEM', 'CVS', 'DUK'],
 ['COP', 'CVX', 'SHEL', 'HL', 'NEM', 'CVS', 'SO']]
```

[16]:
```
# Expected return and volatility for random portfolio weights
from pylab import mpl, plt
```

```python
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)))
```

[17]:

```python
# Optimal portfolio
import scipy.optimize as sco

noa = 7

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,])
eweights
```

[17]:

```
array([0.14285714, 0.14285714, 0.14285714, 0.14285714, 0.14285714,
       0.14285714, 0.14285714])
```

[18]:

```python
# 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
```

[19]:

```python
#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]
```

[20]:
```
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])]))
```

[21]:
```
for portfolio in train_top_5_portfolios:
    sharpe_ratio = train_port_sharpe_ratios[portfolio]
    print(str(portfolio) + " : " + str(sharpe_ratio))
```

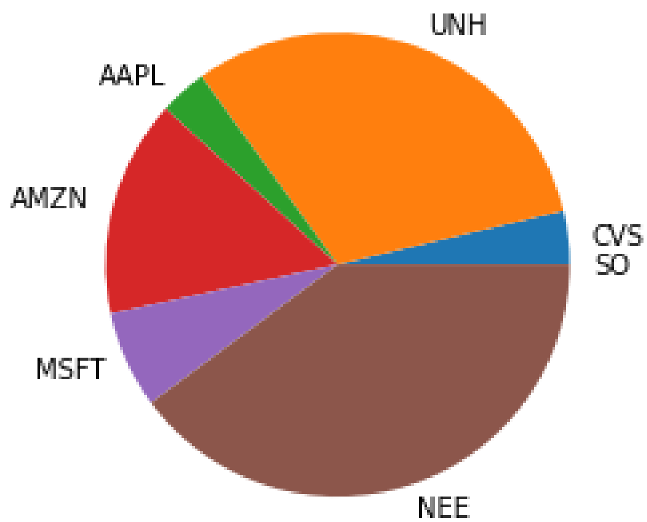
```
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'NEE', 'SO') : 1.549573913288882
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'DUK', 'NEE') : 1.549573618770525
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'NEE', 'SO') : 1.5469583256601187
('SHEL', 'CVS', 'UNH', 'AMZN', 'MSFT', 'NEE', 'SO') : 1.5469582844458225
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'DUK', 'NEE') : 1.5469580824006828
```

[22]:
```
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
```

[23]:
```
#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])
```

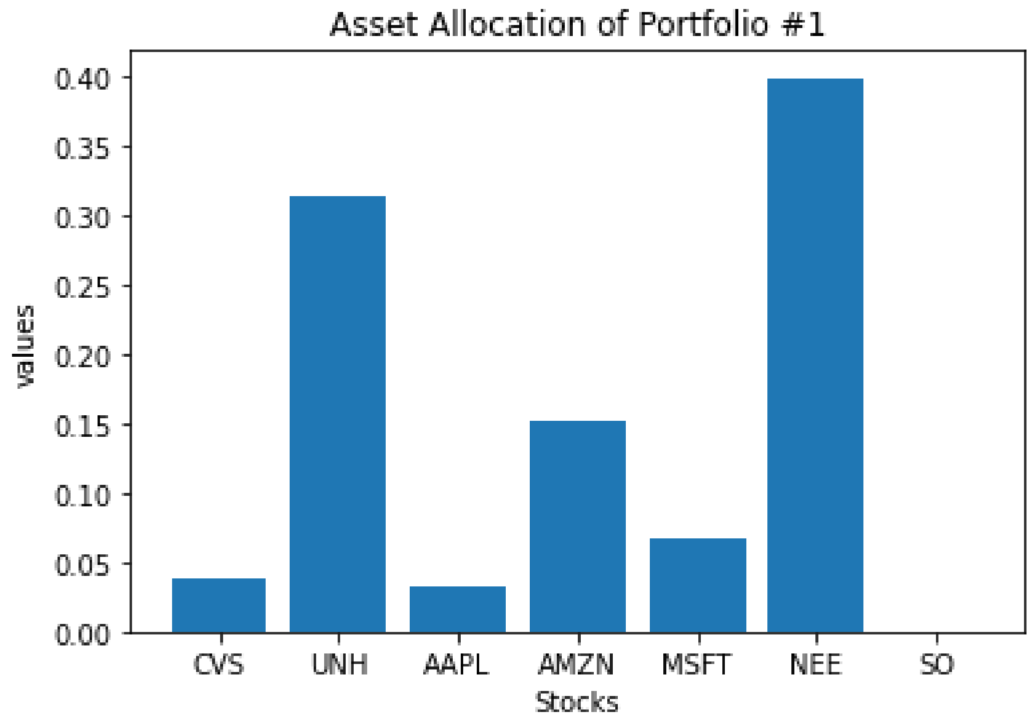
[23]:
```
([<matplotlib.patches.Wedge at 0x7ff291a79be0>,
  <matplotlib.patches.Wedge at 0x7ff291a09160>,
  <matplotlib.patches.Wedge at 0x7ff291a09668>,
  <matplotlib.patches.Wedge at 0x7ff291a09b70>,
  <matplotlib.patches.Wedge at 0x7ff291a120b8>,
  <matplotlib.patches.Wedge at 0x7ff291a125c0>,
  <matplotlib.patches.Wedge at 0x7ff291a12ac8>],
 [Text(1.0924450463634463, 0.12870050767564117, 'CVS'),
```

```
 Text(0.38223080079808097, 1.0314550959306266, 'UNH'),
 Text(-0.7338225066007555, 0.8194537990675156, 'AAPL'),
 Text(-1.0625711732406555, 0.2845039574381649, 'AMZN'),
 Text(-1.0019310192954434, -0.4540200794828288, 'MSFT'),
 Text(0.3447307073041182, -1.0445863963510162, 'NEE'),
 Text(1.0999999999999954, -1.0298943298478347e-07, 'SO')])
```



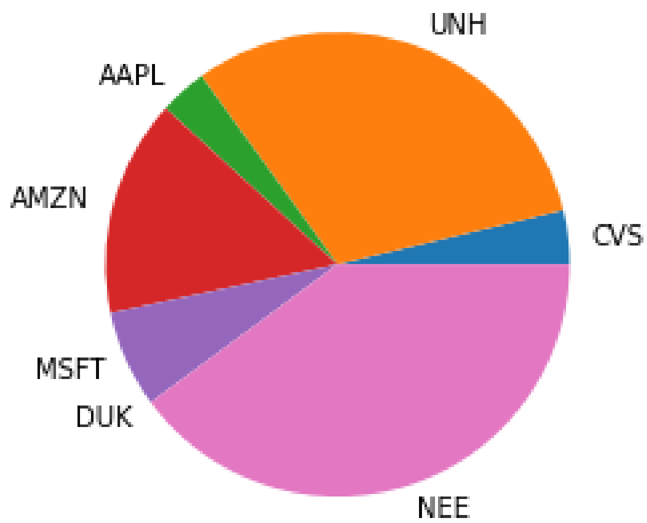
[24]:
```
plt.bar(list(train_top_5_portfolios[0]),
 ↪train_port_weight_dict[train_top_5_portfolios[0]])
plt.title('Asset Allocation of Portfolio #1')
plt.xlabel("Stocks")
plt.ylabel('values')
```

[24]:
```
Text(0, 0.5, 'values')
```



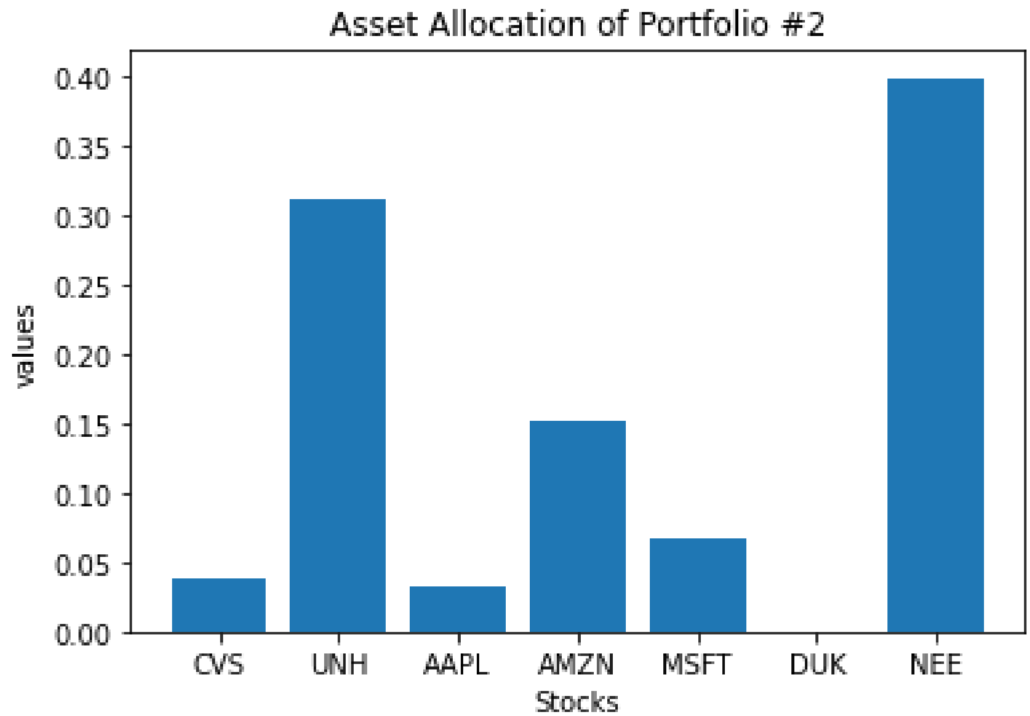
[25]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[1]], labels =␣
↪train_top_5_portfolios[1])
```

[25]:
```
([<matplotlib.patches.Wedge at 0x7ff2919bdf60>,
  <matplotlib.patches.Wedge at 0x7ff2919484e0>,
  <matplotlib.patches.Wedge at 0x7ff2919489e8>,
  <matplotlib.patches.Wedge at 0x7ff291948ef0>,
  <matplotlib.patches.Wedge at 0x7ff291953438>,
  <matplotlib.patches.Wedge at 0x7ff291953940>,
  <matplotlib.patches.Wedge at 0x7ff291953e48>],
 [Text(1.0923749419138924, 0.12929418501471956, 'CVS'),
  Text(0.3818217892069207, 1.0316065729176147, 'UNH'),
  Text(-0.7335540525172217, 0.8196941210204948, 'AAPL'),
  Text(-1.062270006325416, 0.2856263882441551, 'AMZN'),
  Text(-1.002642650315341, -0.45244636783670744, 'MSFT'),
  Text(-0.8848367850447902, -0.6535012347590476, 'DUK'),
  Text(0.3440054281163404, -1.0448254712757024, 'NEE')])
```



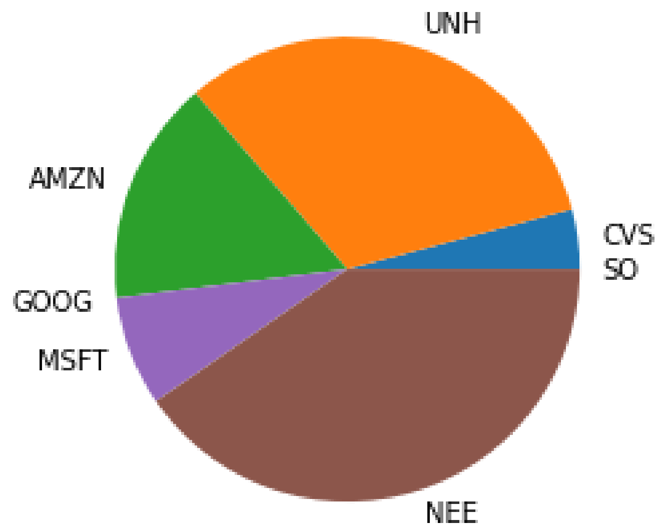
[26]:
```
plt.bar(list(train_top_5_portfolios[1]),␣
 ↪train_port_weight_dict[train_top_5_portfolios[1]])
plt.title('Asset Allocation of Portfolio #2')
plt.xlabel("Stocks")
plt.ylabel('values')
```

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



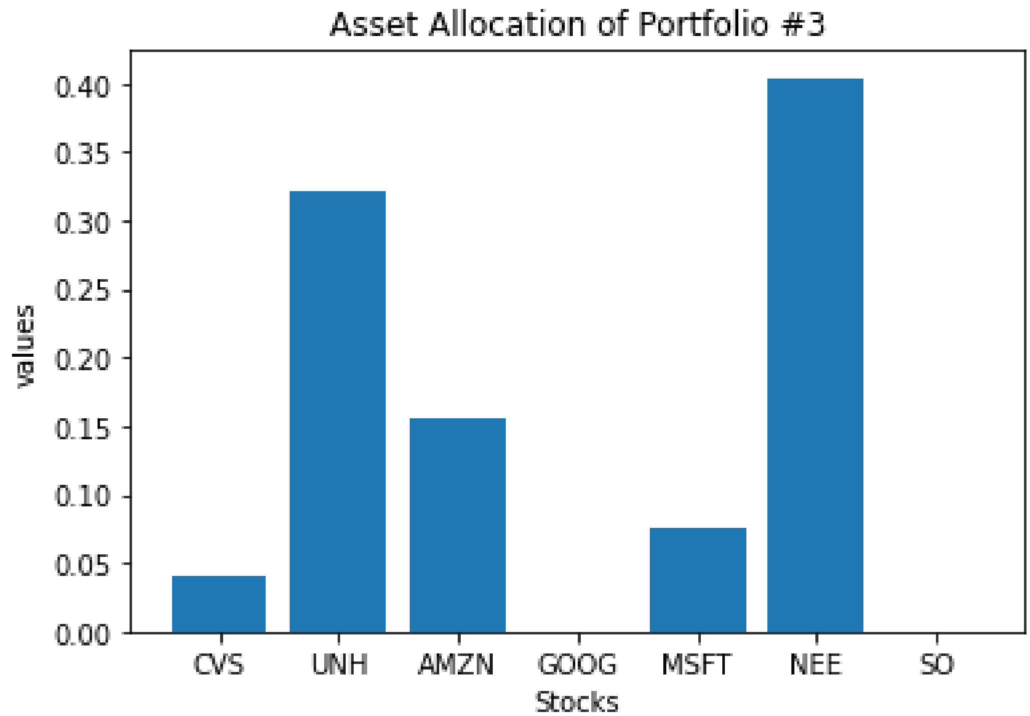
[27]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[2]], labels =␣
 ↪train_top_5_portfolios[2])
```

[27]:
```
([<matplotlib.patches.Wedge at 0x7ff2918857f0>,
  <matplotlib.patches.Wedge at 0x7ff291885d30>,
  <matplotlib.patches.Wedge at 0x7ff291890278>,
  <matplotlib.patches.Wedge at 0x7ff291890780>,
  <matplotlib.patches.Wedge at 0x7ff291890c88>,
  <matplotlib.patches.Wedge at 0x7ff29189a1d0>,
  <matplotlib.patches.Wedge at 0x7ff29189a6d8>],
 [Text(1.0906780503193585, 0.14290343086001503, 'CVS'),
  Text(0.3236617440901387, 1.0513054149068812, 'UNH'),
  Text(-1.0267801699745027, 0.3946168807174011, 'AMZN'),
  Text(-1.091549128414389, -0.13609004466818145, 'GOOG'),
  Text(-1.0278467558945792, -0.39183037962489514, 'MSFT'),
  Text(0.3273730011451989, -1.0501556637571337, 'NEE'),
  Text(1.0999999999999892, 1.5448414929211732e-07, 'SO')])
```



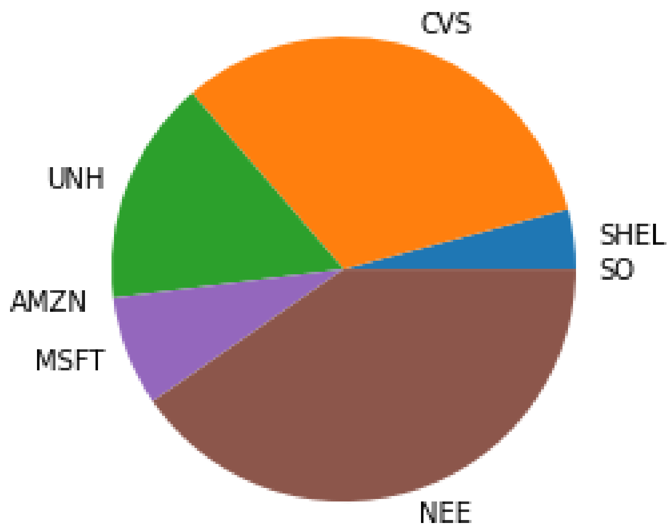

```
[28]: plt.bar(list(train_top_5_portfolios[2]),
       ↪train_port_weight_dict[train_top_5_portfolios[2]])
      plt.title('Asset Allocation of Portfolio #3')
      plt.xlabel("Stocks")
      plt.ylabel('values')
```

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



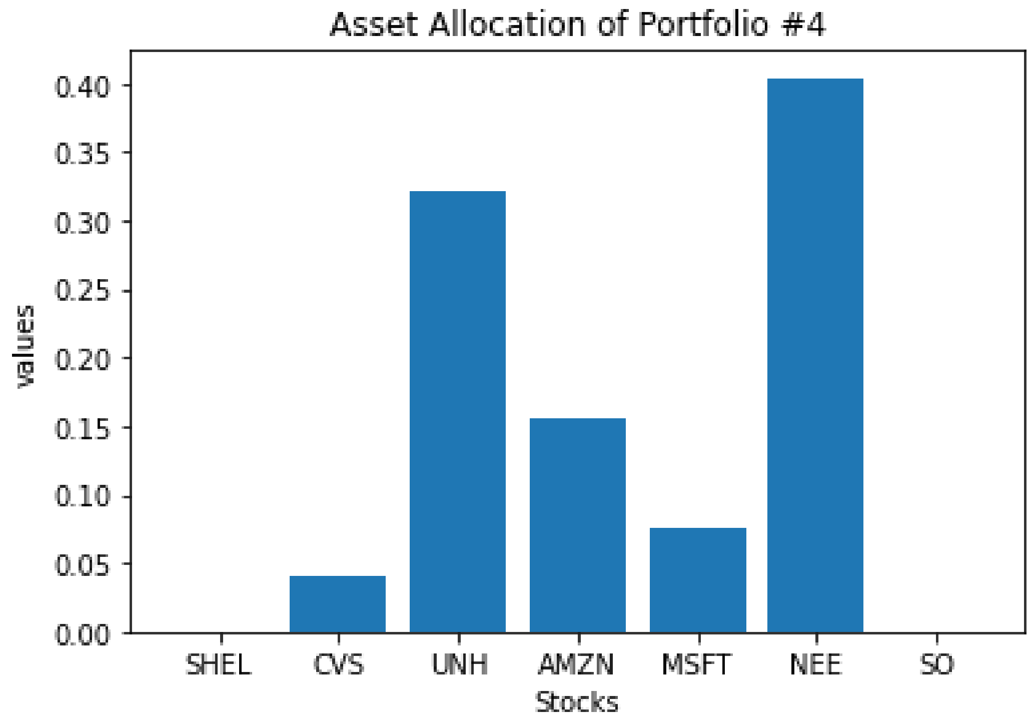
[29]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[2]], labels =␣
↪train_top_5_portfolios[3])
```

[29]:
```
([<matplotlib.patches.Wedge at 0x7ff2917c1b38>,
  <matplotlib.patches.Wedge at 0x7ff2917cf0b8>,
  <matplotlib.patches.Wedge at 0x7ff2917cf5c0>,
  <matplotlib.patches.Wedge at 0x7ff2917cfac8>,
  <matplotlib.patches.Wedge at 0x7ff2917cffd0>,
  <matplotlib.patches.Wedge at 0x7ff2917db518>,
  <matplotlib.patches.Wedge at 0x7ff2917dba20>],
 [Text(1.0906780503193585, 0.14290343086001503, 'SHEL'),
  Text(0.3236617440901387, 1.0513054149068812, 'CVS'),
  Text(-1.0267801699745027, 0.3946168807174011, 'UNH'),
  Text(-1.091549128414389, -0.13609004466818145, 'AMZN'),
  Text(-1.0278467558945792, -0.39183037962489514, 'MSFT'),
  Text(0.3273730011451989, -1.0501556637571337, 'NEE'),
  Text(1.0999999999999892, 1.5448414929211732e-07, 'SO')])
```



[30]:
```
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')
```

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



[31]:
```
plt.pie(train_port_weight_dict[train_top_5_portfolios[2]], labels =
→train_top_5_portfolios[4])
```

[31]:
```
([<matplotlib.patches.Wedge at 0x7ff29170efd0>,
  <matplotlib.patches.Wedge at 0x7ff29171c4a8>,
  <matplotlib.patches.Wedge at 0x7ff29171c9b0>,
  <matplotlib.patches.Wedge at 0x7ff29171ceb8>,
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  <matplotlib.patches.Wedge at 0x7ff291726908>,
  <matplotlib.patches.Wedge at 0x7ff291726e10>],
 [Text(1.0906780503193585, 0.14290343086001503, 'CVS'),
  Text(0.3236617440901387, 1.0513054149068812, 'UNH'),
  Text(-1.0267801699745027, 0.3946168807174011, 'AMZN'),
  Text(-1.091549128414389, -0.13609004466818145, 'GOOG'),
  Text(-1.0278467558945792, -0.39183037962489514, 'MSFT'),
  Text(0.3273730011451989, -1.0501556637571337, 'DUK'),
  Text(1.0999999999999892, 1.5448414929211732e-07, 'NEE')])
```
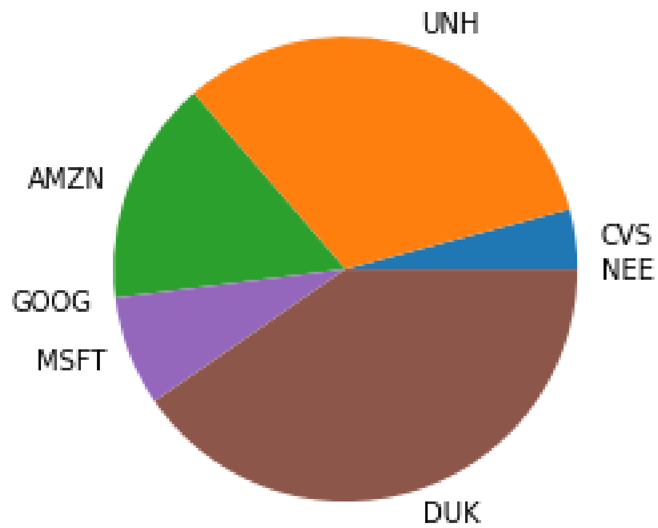
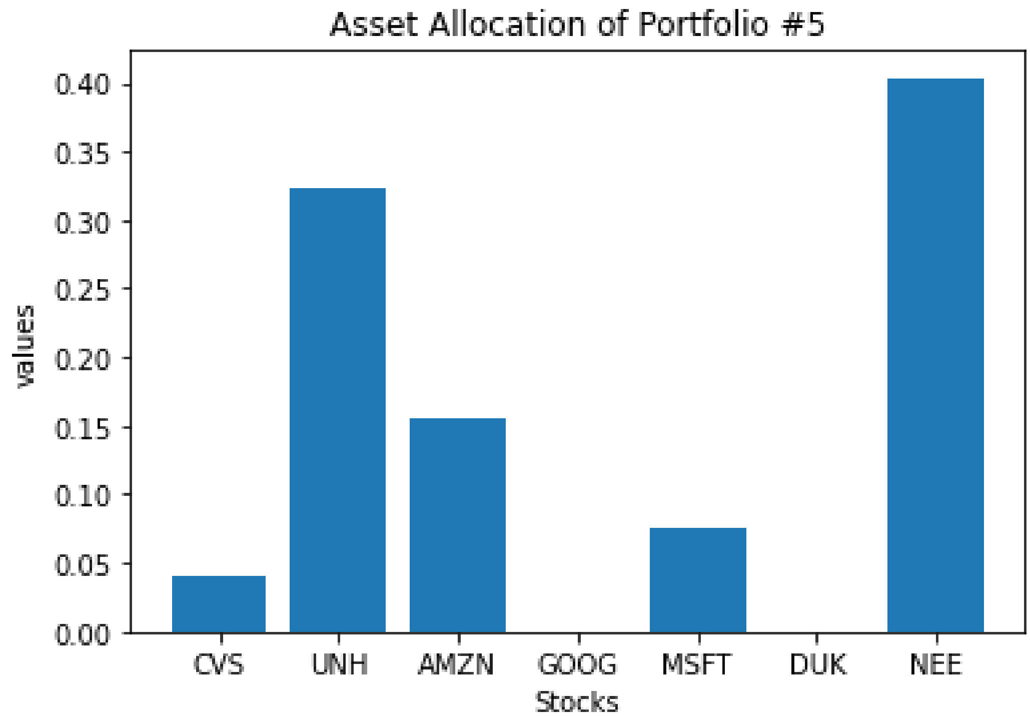



[32]:
```
plt.bar(list(train_top_5_portfolios[4]),␣
↪train_port_weight_dict[train_top_5_portfolios[4]])
plt.title('Asset Allocation of Portfolio #5')
plt.xlabel("Stocks")
plt.ylabel('values')
```

[32]:
```
Text(0, 0.5, 'values')
```

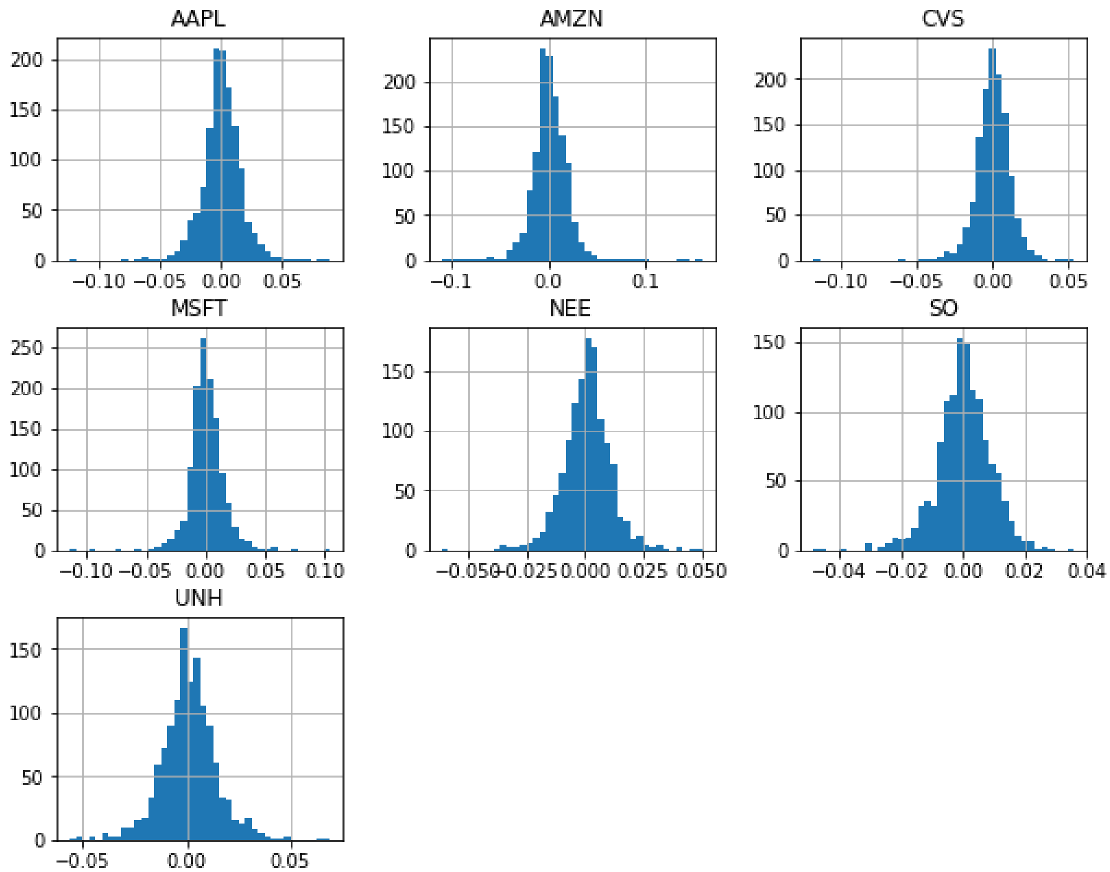


[33]:
```
#Since all the portfolio's are very similar let's focus on the one with the
↪highest sharpe ratio and see how it's distributed

top_port = train_top_5_portfolios[0]
```

[34]:
```
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))
```

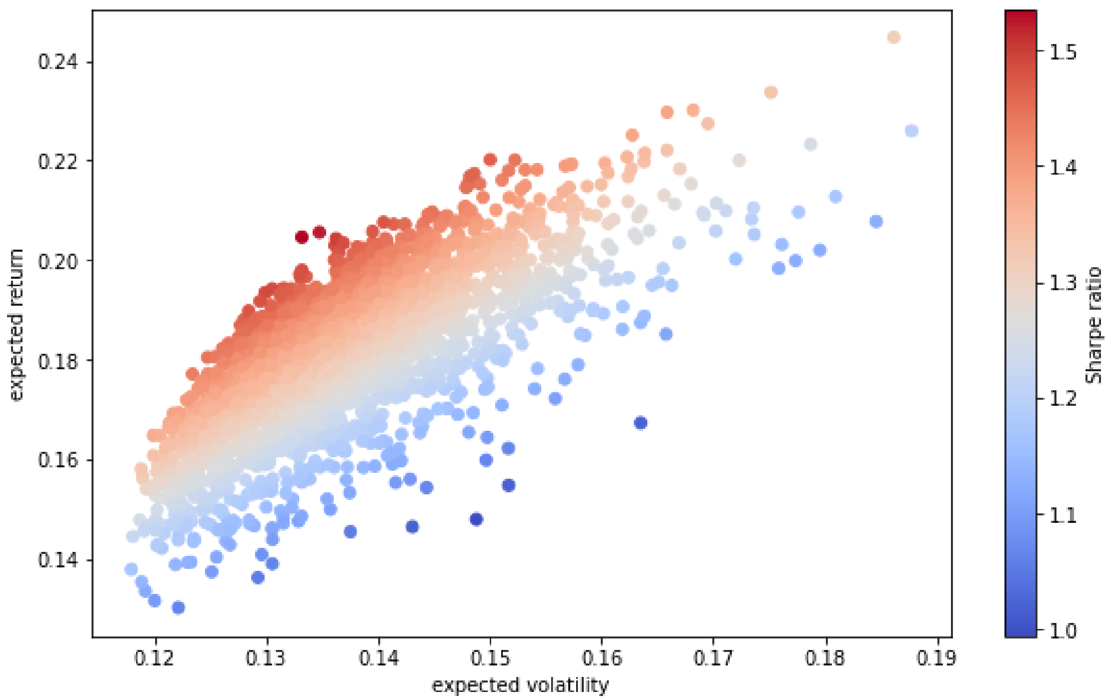
```
Portfolio Returns: 0.21248279285555638
Portfolio Volatility: 0.13712336729041458
```

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



[36]:
```
#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)
```



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

[37]:
```
#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)
```

[37]:
```
                 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
```

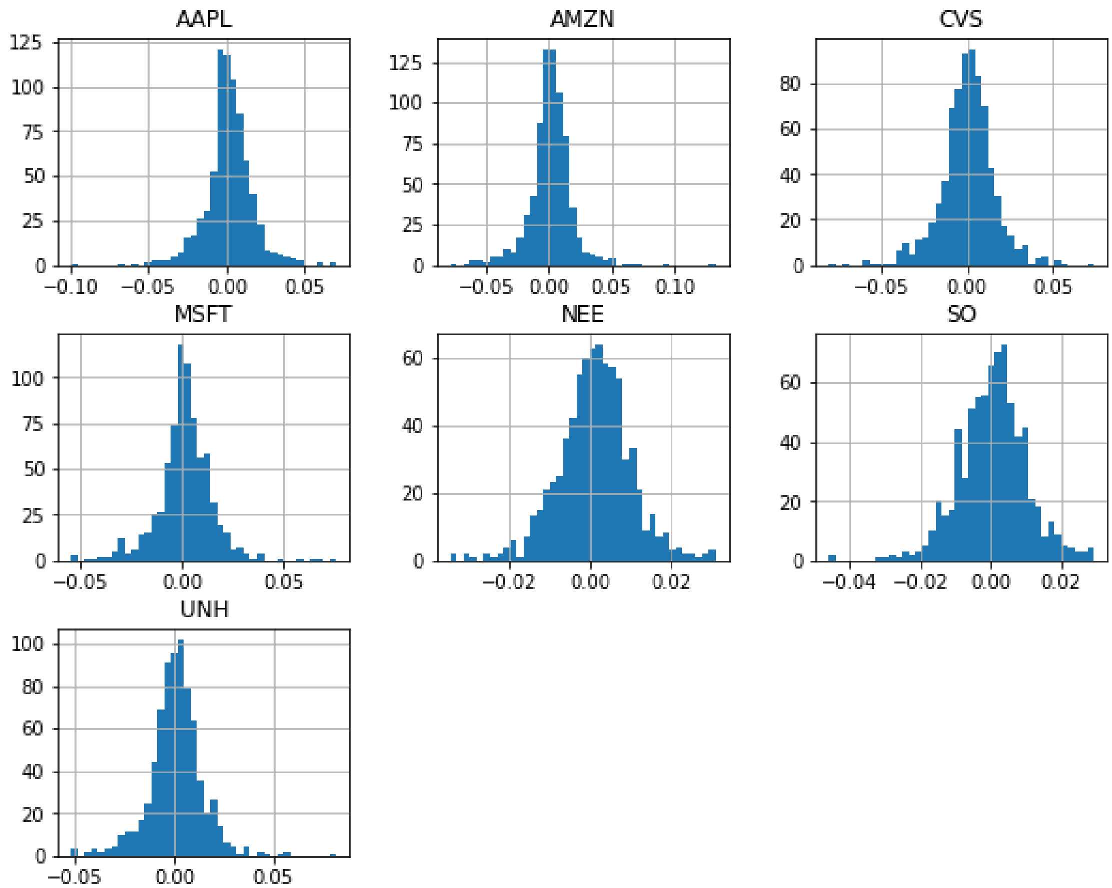
[38]:
```
#Now let's take a look at how the top portfolios found using the training␣
↪dataset performed in the PRE-COVID testing dataset

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))
```

```
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'NEE', 'SO') : 1.927663382902878
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'DUK', 'NEE') : 1.927857134817072
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'NEE', 'SO') : 1.8993387983903505
('SHEL', 'CVS', 'UNH', 'AMZN', 'MSFT', 'NEE', 'SO') : 1.8995667892847548
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'DUK', 'NEE') : 1.8989248528103253
```

[39]:
```
#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: 0.2512289234629903
Portfolio Volatility: 0.13032821274255021
```

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



0.0.3 Now let's see how the portfolios with highest sharpe ratios performed in the COVID testing dataset

[41]:
```
#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)
```

[41]:

Date	COP	CVX	SHEL	XOM	CDE	HL \
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
```

[42]:
```
#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]
```

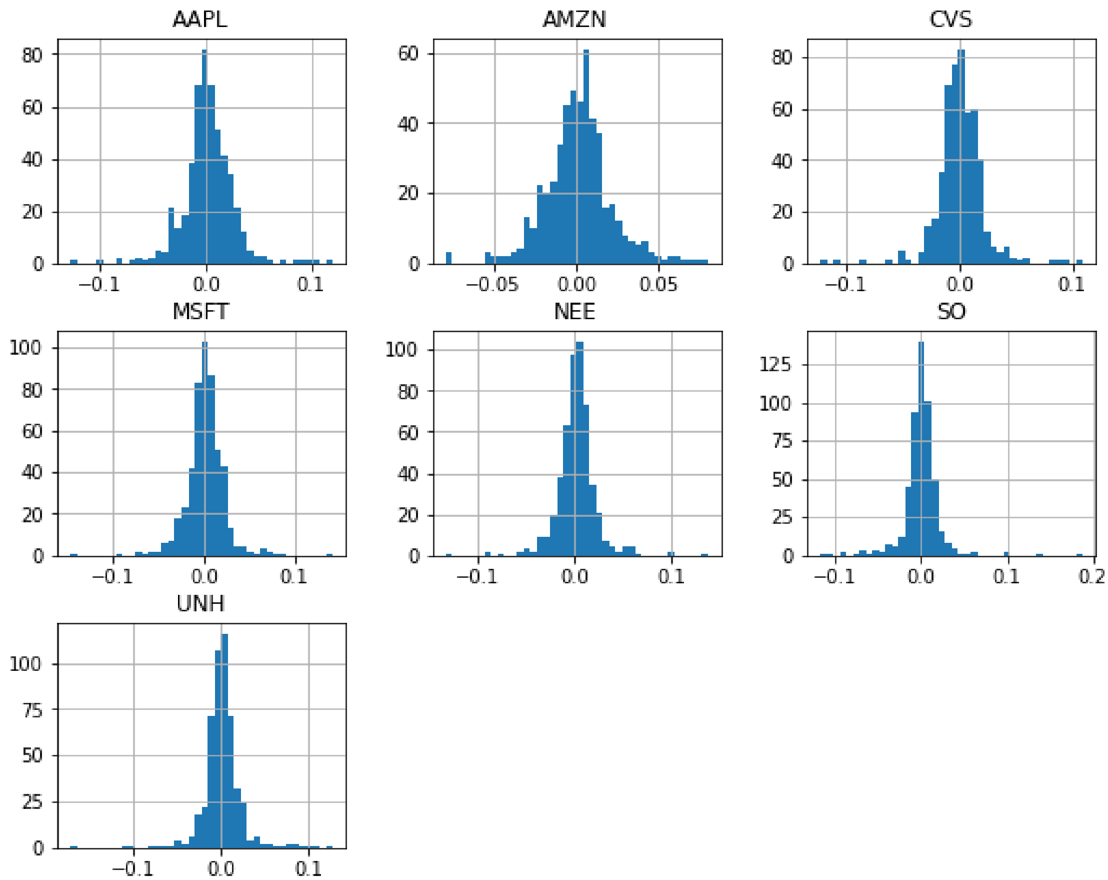
```
    portfolio_df = COVID_TESTING_df[list(portfolio)]
    sharpe_ratio = -min_func_sharpe(weights, portfolio_df)

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

```
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'NEE', 'SO') : 0.9943844820853028
('CVS', 'UNH', 'AAPL', 'AMZN', 'MSFT', 'DUK', 'NEE') : 0.9943122412682911
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'NEE', 'SO') : 0.9775785824135252
('SHEL', 'CVS', 'UNH', 'AMZN', 'MSFT', 'NEE', 'SO') : 0.977593949164001
('CVS', 'UNH', 'AMZN', 'GOOG', 'MSFT', 'DUK', 'NEE') : 0.9776229348307766
```

[43]:
```
#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: 0.2761959038778191
Portfolio Volatility: 0.27775564568205496
```

[44]:
```
port_rets = COVID_rets[list(top_port)]
port_rets.hist(bins = 40, figsize = (10, 8));
```


AAPL
AMZN
CVS
MSFT
NEE
SO
UNH