Risky_Stock_Portfolio_Generator

January 3, 2022

[1]:
```python
from IPython.display import display, Math, Latex

import pandas as pd
import numpy as np
import numpy_financial as npf
import yfinance as yf
import matplotlib.pyplot as plt
from datetime import datetime
```

0.1 Group Assignment

0.1.1 Team Number: 16

0.1.2 Team Member Names: Stephen Chen, Bhavya Shah, Alex Liu

0.1.3 Team Strategy Chosen: RISKY

[2]:
```python
# Importing csv file with tickers and reformatting dataframe
ticker_list = pd.read_csv("Tickers.csv")
add_columns = pd.DataFrame({ticker_list.columns[0]:ticker_list.columns[0]},␣
↪index=[len(ticker_list)])
ticker_list = ticker_list.append(add_columns)
ticker_list.columns=['Tickers']
```

[3]:
```python
# Dropping duplicate tickers and resetting index
ticker_list = pd.DataFrame ({'Tickers': ticker_list.Tickers.drop_duplicates()})
ticker_list.reset_index(inplace=True)
ticker_list = ticker_list.iloc[: , 1:]
```

[4]:
```python
# displaying the list of tickers
ticker_list
```

[4]:
```
   Tickers
0     ABBV
1      ABT
2      ACN
3      AGN
4      AIG
..     …
```

```
57     UNH
58     UNP
59     UPS
60     USB
61    AAPL

[62 rows x 1 columns]
```

[5]:
```
# identifying non-American stocks, converting tickers to American (if possible)
for i in range(0, len(ticker_list)):
    ticker = str(ticker_list.iloc[i, 0])

    # finds the period in the stock tickers
    get_position = ticker.find('.')

    # if there is a period in the string (meaning that it's not an American␣
 ↪stock)
    if (get_position != -1):
        ticker_list.iloc[i, 0] = ticker[:get_position]
```

[6]:
```
sector_list = pd.DataFrame(columns = ['Sectors'])

# function that determines the standard deviation of each stock
def get_deviation(ticker):
    stock_ticker = ticker
    stock_hist = stock_ticker.history(start='2018-01-01', end='2021-11-19')
    stock_close = stock_hist['Close']

    # grouping Close prices by months
    stock_close.index = pd.to_datetime(stock_close.index)
    monthly_close = stock_close.groupby(stock_close.index.to_period('m')).
 ↪head(1)

    # returning the standard deviation based off of percent change
    return (monthly_close.pct_change()*100).std()

i = 0

# For loop to find the standard deviation of all the stocks in ticker list
for i in range (len(ticker_list)):
    stock = yf.Ticker(ticker_list.iloc[i, 0])
    sector = stock.info.get('sector')
    add_data = pd.DataFrame({'Sectors':sector,
                             'Standard Deviation':␣
 ↪get_deviation(stock)},index=[i])
    sector_list = sector_list.append(add_data)
```

```
- AGN: No data found, symbol may be delisted
```

```
- CELG: No data found, symbol may be delisted
- PCLN: No data found for this date range, symbol may be delisted
- RTN: No data found, symbol may be delisted
```

[7]:
```python
sector_list
```

[7]:
```
               Sectors  Standard Deviation
0           Healthcare            8.569739
1           Healthcare            6.070936
2           Technology            6.994099
3                 None                 NaN
4   Financial Services           12.029141
..                 …                   …
57          Healthcare            7.253478
58         Industrials            7.524285
59         Industrials            9.225229
60  Financial Services            8.331631
61          Technology           10.091369

[62 rows x 2 columns]
```

[8]:
```python
# Concatenating ticker list to standard deviation list
ticker_list = pd.concat([ticker_list, sector_list], join='inner',axis=1)
```

[9]:
```python
# Removing stocks without sectors
ticker_list = ticker_list[ticker_list.Sectors.notnull()]
ticker_list.set_index('Sectors', inplace=True)
```

[10]:
```python
# Outputting ticker list with standard deviation list
ticker_list
```

[10]:
```
                       Tickers  Standard Deviation
Sectors
Healthcare                ABBV            8.569739
Healthcare                 ABT            6.070936
Technology                 ACN            6.994099
Financial Services         AIG           12.029141
Consumer Cyclical         AMZN            8.187451
Financial Services         AXP            8.920671
Industrials                 BA           13.633314
Financial Services         BAC            9.501078
Healthcare                BIIB           11.080848
Financial Services          BK            7.329313
Financial Services         BLK            7.788556
Healthcare                 BMY            5.935182
Financial Services           C           11.555252
Industrials                CAT            8.394303
Consumer Defensive          CL            4.817024
```

```
Communication Services   CMCSA              7.578767
Financial Services         COF             12.107918
Energy                     COP             12.924563
Consumer Defensive        COST              5.091330
Technology                CSCO              7.768640
Healthcare                 CVS              7.779541
Consumer Cyclical           GM             12.174480
Communication Services    GOOG              7.670060
Financial Services         JPM              8.063898
Energy                     KMI              8.874310
Consumer Defensive          KO              5.638519
Healthcare                 LLY              7.440416
Industrials                LMT              6.520709
Consumer Defensive          MO              6.760152
Financial Services         MON              0.472669
Healthcare                 MRK              5.166594
Financial Services          MS              9.995934
Technology                MSFT              6.305217
Utilities                  NEE              5.720650
Consumer Cyclical          NKE              7.364820
Technology                ORCL              5.821712
Energy                     OXY             19.543815
Consumer Defensive         PEP              5.026444
Healthcare                 PFE              6.712639
Consumer Defensive          PG              4.376677
Consumer Defensive          PM              7.570634
Financial Services        PYPL              9.442428
Technology                QCOM             12.599123
Technology                SHOP             14.632376
Consumer Cyclical         SBUX              7.669894
Energy                     SLB             15.023794
Utilities                   SO              6.147260
Real Estate                SPG             13.402588
Communication Services       T              5.640447
Financial Services          TD              7.024688
Consumer Defensive         TGT              8.669339
Technology                 TXN              6.685049
Healthcare                 UNH              7.253478
Industrials                UNP              7.524285
Industrials                UPS              9.225229
Financial Services         USB              8.331631
Technology                AAPL             10.091369
```

[11]:
```
# dropping stocks that have insufficient data

# creating a duplicate ticker list to transform
duplicate_list = ticker_list.copy()
```

```python
# resetting the index of the duplicate list
duplicate_list.reset_index(inplace=True)

# list of indices to drop later
drop = []
```

[12]:
```python
# Apple is a company that has sufficient stock information. We use Apple as a␣
↪reference for how many entries of information a stock should have.

# getting the ticker, history and close price information of Apple
apple = yf.Ticker('AAPL')
apple_hist = apple.history(start="2018-01-01", end="2021-11-19")
apple_close = apple_hist['Close']

# getting the length of the Close Price of Apple Dataframe (this is how much␣
↪data should be in each dataframe)
desired_length = len(apple_close)
```

[13]:
```python
# for-loop to check each stock to see if they have a sufficient amount of data
for i in range (0, len(ticker_list)):

    # getting the ticker, ticker history and close price information of each␣
↪stock.
    ticker = yf.Ticker(ticker_list.iloc[i, 0])
    t_hist = ticker.history(start="2018-01-01", end="2021-11-19")
    ticker_close = t_hist['Close']

    # if there is an insufficient amount of data, append to the list of indices␣
↪to be dropped
    if (len(ticker_close) != desired_length):
        drop.append(duplicate_list.index[i])
```

[14]:
```python
# dropping the stocks with an insufficient amount of information
duplicate_list.drop(drop, inplace=True)

# re-indexing and re-formatting the duplicate dataframe
duplicate_list.index = duplicate_list['Sectors']
duplicate_list.drop(columns=['Sectors'], inplace=True)

# removing the undesired stocks from the ticker list
ticker_list = duplicate_list
```

[15]:
```python
# displaying the ticker list
ticker_list
```

[15]:

Sectors	Tickers	Standard Deviation
Healthcare	ABBV	8.569739
Healthcare	ABT	6.070936
Technology	ACN	6.994099
Financial Services	AIG	12.029141
Consumer Cyclical	AMZN	8.187451
Financial Services	AXP	8.920671
Industrials	BA	13.633314
Financial Services	BAC	9.501078
Healthcare	BIIB	11.080848
Financial Services	BK	7.329313
Financial Services	BLK	7.788556
Healthcare	BMY	5.935182
Financial Services	C	11.555252
Industrials	CAT	8.394303
Consumer Defensive	CL	4.817024
Communication Services	CMCSA	7.578767
Financial Services	COF	12.107918
Energy	COP	12.924563
Consumer Defensive	COST	5.091330
Technology	CSCO	7.768640
Healthcare	CVS	7.779541
Consumer Cyclical	GM	12.174480
Communication Services	GOOG	7.670060
Financial Services	JPM	8.063898
Energy	KMI	8.874310
Consumer Defensive	KO	5.638519
Healthcare	LLY	7.440416
Industrials	LMT	6.520709
Consumer Defensive	MO	6.760152
Healthcare	MRK	5.166594
Financial Services	MS	9.995934
Technology	MSFT	6.305217
Utilities	NEE	5.720650
Consumer Cyclical	NKE	7.364820
Technology	ORCL	5.821712
Energy	OXY	19.543815
Consumer Defensive	PEP	5.026444
Healthcare	PFE	6.712639
Consumer Defensive	PG	4.376677
Consumer Defensive	PM	7.570634
Financial Services	PYPL	9.442428
Technology	QCOM	12.599123
Technology	SHOP	14.632376
Consumer Cyclical	SBUX	7.669894
Energy	SLB	15.023794

```
Utilities                    SO           6.147260
Real Estate                 SPG          13.402588
Communication Services        T           5.640447
Financial Services           TD           7.024688
Consumer Defensive          TGT           8.669339
Technology                  TXN           6.685049
Healthcare                  UNH           7.253478
Industrials                 UNP           7.524285
Financial Services          USB           8.331631
Technology                 AAPL          10.091369
```

[16]:
```
# placeholder volume column
ticker_list["Volume"] = None

# loop to calculate the average daily volume of each stock
for i in range (0, len(ticker_list)):

    # getting the number of days between June 2, 2021 and October 22, 2021
    num_days = int(str(pd.to_datetime('2021-07-02') - pd.
 ↪to_datetime('2021-10-22'))[1:4])

    # getting each ticker's information
    ticker = yf.Ticker(ticker_list.iloc[i, 0])
    ticker_hist = ticker.history(start="2021-07-02", end="2021-10-22")
    ticker_volume = ticker_hist['Volume'].sum()/num_days
    ticker_list.iloc[i, -1] = ticker_volume

# filtering for the tickers that fit our requirement
ticker_list = ticker_list[(ticker_list["Volume"] >= 10000)]
```

[17]:
```
# Filtering for each sector and sorting each sector from highest to lowest␣
 ↪standard deviation
def sort_list (industry_list, industry):
    industry_list = ticker_list.filter(like = industry, axis=0)
    industry_list = industry_list.sort_values(by=['Standard Deviation'],␣
 ↪ascending = False)
    return industry_list
```

[18]:
```
energy_list = sort_list (ticker_list, 'Energy')
energy_list
```

[18]:

	Tickers	Standard Deviation	Volume
Sectors			
Energy	OXY	19.543815	11707057.142857
Energy	SLB	15.023794	7528641.964286
Energy	COP	12.924563	6067660.714286

```
Energy      KMI           8.874310   9776673.214286
```

[19]:
```python
financial_list = sort_list (ticker_list, 'Financial Services')
financial_list
```

[19]:
```
                   Tickers  Standard Deviation           Volume
Sectors
Financial Services     COF           12.107918   1965058.035714
Financial Services     AIG           12.029141   2983665.178571
Financial Services       C           11.555252  12883508.928571
Financial Services      MS            9.995934   5997000.892857
Financial Services     BAC            9.501078  33489260.714286
Financial Services    PYPL            9.442428   4678679.464286
Financial Services     AXP            8.920671   2532703.571429
Financial Services     USB            8.331631   3711789.285714
Financial Services     JPM            8.063898   7968159.821429
Financial Services     BLK            7.788556        362068.75
Financial Services      BK            7.329313   3396391.964286
Financial Services      TD            7.024688       1057731.25
```

[20]:
```python
tech_list = sort_list (ticker_list, 'Technology')
tech_list
```

[20]:
```
           Tickers  Standard Deviation           Volume
Sectors
Technology    SHOP           14.632376    691973.214286
Technology    QCOM           12.599123   4954920.535714
Technology    AAPL           10.091369  55696846.428571
Technology    CSCO            7.768640  10937365.178571
Technology     ACN            6.994099   1248614.285714
Technology     TXN            6.685049        2425787.5
Technology    MSFT            6.305217  15980571.428571
Technology    ORCL            5.821712   7671951.785714
```

[21]:
```python
healthcare_list = sort_list (ticker_list, 'Healthcare')
healthcare_list
```

[21]:
```
           Tickers  Standard Deviation           Volume
Sectors
Healthcare    BIIB           11.080848    752603.571429
Healthcare    ABBV            8.569739   4826476.785714
Healthcare     CVS            7.779541   3637359.821429
Healthcare     LLY            7.440416       1768306.25
Healthcare     UNH            7.253478   1778942.857143
Healthcare     PFE            6.712639  21327650.892857
Healthcare     ABT            6.070936   3254866.964286
Healthcare     BMY            5.935182   6440792.857143
```

```
Healthcare     MRK            5.166594   8697586.607143
```

[22]:
```python
estate_list = sort_list (ticker_list, 'Real Estate')
estate_list
```

[22]:
```
            Tickers  Standard Deviation      Volume
Sectors
Real Estate     SPG           13.402588  1387918.75
```

[23]:
```python
industry_list = sort_list (ticker_list, 'Industrials')
industry_list
```

[23]:
```
            Tickers  Standard Deviation          Volume
Sectors
Industrials      BA           13.633314  6776169.642857
Industrials     CAT            8.394303  2384585.714286
Industrials     UNP            7.524285  2148769.642857
Industrials     LMT            6.520709   787491.964286
```

[24]:
```python
utilities_list = sort_list(ticker_list, 'Utilities')
utilities_list
```

[24]:
```
          Tickers  Standard Deviation          Volume
Sectors
Utilities      SO             6.14726  2736672.321429
Utilities     NEE             5.72065  4644516.964286
```

[25]:
```python
communication_list = sort_list(ticker_list,'Communication Services')
communication_list
```

[25]:
```
                       Tickers  Standard Deviation         Volume
Sectors
Communication Services    GOOG            7.670060  723633.035714
Communication Services   CMCSA            7.578767    10583018.75
Communication Services       T            5.640447    24657718.75
```

[26]:
```python
materials_list = sort_list(ticker_list,'Basic Materials')
materials_list
```

[26]:
```
Empty DataFrame
Columns: [Tickers, Standard Deviation, Volume]
Index: []
```

[27]:
```python
consumer_list = sort_list(ticker_list,'Consumer Defensive')
consumer_list
```

[27]:
```
                   Tickers  Standard Deviation          Volume
Sectors
```

```
Consumer Defensive     TGT           8.669339  2036626.785714
Consumer Defensive      PM           7.570634  2618207.142857
Consumer Defensive      MO           6.760152  4468792.857143
Consumer Defensive      KO           5.638519  9514454.464286
Consumer Defensive    COST           5.091330  1203228.571429
Consumer Defensive     PEP           5.026444  2789961.607143
Consumer Defensive      CL           4.817024  2655066.071429
Consumer Defensive      PG           4.376677  4636135.714286
```

[28]:
```python
cyclical_list = sort_list(ticker_list,'Consumer Cyclical')
cyclical_list
```

[28]:
```
                  Tickers  Standard Deviation          Volume
Sectors
Consumer Cyclical      GM           12.174480  11848326.785714
Consumer Cyclical    AMZN            8.187451       2211843.75
Consumer Cyclical    SBUX            7.669894   3825971.428571
Consumer Cyclical     NKE            7.364820   4249422.321429
```

[29]:
```python
# getting the list of the sectors
sectors_list = [energy_list, financial_list, tech_list, healthcare_list,␣
↪estate_list, industry_list, utilities_list, communication_list,␣
↪materials_list, consumer_list]
```

[30]:
```python
# find the sector with the highest standard deviation
def find_highest_sector_deviation(list_of_sectors):

    sector_deviation = []

    # list of sectors isn't empty
    if (len(list_of_sectors) != 0):

        # temporary variables for the highest deviation, along with the sector␣
↪with the highest deviation
        highest_deviation = -100000000
        highest_deviation_sector = None

        # for-loop which loops through each sector
        for i in range (0, len(list_of_sectors)):

            # temporary dataframe to store values
            temp = pd.DataFrame()

            # dataframe with each stock in a specific sector
            sector = list_of_sectors[i]
```

```
            # getting the average deviation of each stock/standard deviation of␣
↪the sector
            temp_deviation = sector['Standard Deviation'].sum()/len(sector)

            # determining if that sector has the highest deviation or not, if␣
↪it is, change the values
            if (temp_deviation > highest_deviation):
                highest_deviation = temp_deviation
                highest_deviation_sector = sector

            sector_deviation.append([sector.index[0], temp_deviation])

        # return the sector with the highest deviation
        return highest_deviation_sector, sector_deviation

    # list of sectors is empty
    else:

        # return 0
        return 0
```

[31]:
```
# filter out sectors without any stocks
filtered_sectors_list = []

# for-loop to get rid of any sectors without any stocks in them (lowers␣
↪run-time)
for i in range (0, len(sectors_list)):

    # if the sector list isn't empty, add the sector to the filtered list
    if (len(sectors_list[i]) != 0):
        filtered_sectors_list.append(sectors_list[i])
```

[32]:
```
high_deviation_sector = find_highest_sector_deviation(filtered_sectors_list)[0]
high_deviation_sector
```

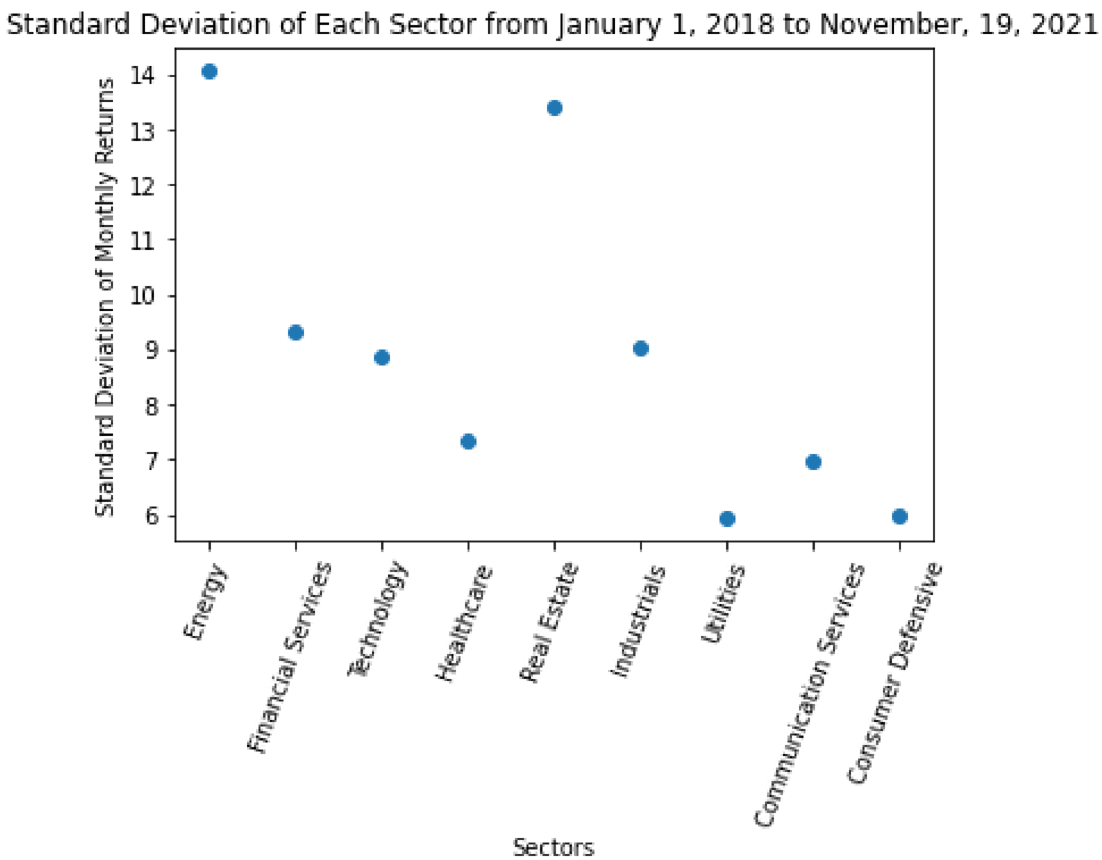
[32]:
```
        Tickers  Standard Deviation         Volume
Sectors
Energy      OXY           19.543815  11707057.142857
Energy      SLB           15.023794   7528641.964286
Energy      COP           12.924563   6067660.714286
Energy      KMI            8.874310   9776673.214286
```

[33]:
```
# getting the standard deviation information for each sector
sector_deviation = find_highest_sector_deviation(filtered_sectors_list)[1]

# creating a scatterplot with the data points for standard deviation
plt.scatter(*zip(*sector_deviation))
```

```python
# formatting the graph
plt.title('Standard Deviation of Each Sector from January 1, 2018 to November,␣
↪19, 2021')
plt.xlabel('Sectors')
plt.ylabel('Standard Deviation of Monthly Returns')
plt.xticks(rotation=70)

# displaying the graph
plt.show()
```



Our methodology behind creating a risky portfolio revolves around finding the riskiest sectors that are correlated to each other and limiting both the inter-industry diversification and individual stocks diversification. To limit the amount of inter-industry diversification, we first grouped the stocks based on their sector. After grouping the stocks by sector, we needed to sort the sectors based on risk, so that we can prioritize the sector with the highest risk when forming our portfolio. To accomplish this, we calculated the standard deviation of each sector, which can be seen from the graph above. We decided to use 2018-01-01 to 2021-11-19 as the time period, as the data is recent enough to revelant, while at the same time provides a large enough sample size to which we can make accurate assumptions. We used standard deviation instead of beta as standard deviation measures the unconditional risk of returns, while beta measures conditional risk. To expand, standard deviation measures the volatility of a stock, by calculating the degree to which the stock fluctuates from its mean return, while beta compares the risk to that of the overall market, or another benchmark. In this case, we were more interested in how much the stocks themselves fluctuate, as opposed to how they compare to the market, so we chose standard deviation. Now, we can use the sectors and standard deviation for the stocks to help create a risky portfolio later on.

[34]:
```
# Removes the sector with the highest standard deviation for the sector list
new_filtered = []

for i in range (0, len(filtered_sectors_list)):
    if (filtered_sectors_list[i].index[0] != high_deviation_sector.index[0]):
        new_filtered.append(filtered_sectors_list[i])

new_filtered
```

[34]:
```
[                    Tickers  Standard Deviation          Volume
 Sectors
 Financial Services     COF           12.107918   1965058.035714
 Financial Services     AIG           12.029141   2983665.178571
 Financial Services       C           11.555252  12883508.928571
 Financial Services      MS            9.995934   5997000.892857
 Financial Services     BAC            9.501078  33489260.714286
 Financial Services    PYPL            9.442428   4678679.464286
 Financial Services     AXP            8.920671   2532703.571429
 Financial Services     USB            8.331631   3711789.285714
 Financial Services     JPM            8.063898   7968159.821429
 Financial Services     BLK            7.788556        362068.75
 Financial Services      BK            7.329313   3396391.964286
 Financial Services      TD            7.024688       1057731.25,
             Tickers  Standard Deviation          Volume
 Sectors
 Technology     SHOP           14.632376    691973.214286
 Technology     QCOM           12.599123   4954920.535714
 Technology     AAPL           10.091369  55696846.428571
 Technology     CSCO            7.768640  10937365.178571
 Technology      ACN            6.994099   1248614.285714
 Technology      TXN            6.685049        2425787.5
 Technology     MSFT            6.305217  15980571.428571
 Technology     ORCL            5.821712   7671951.785714,
             Tickers  Standard Deviation          Volume
 Sectors
 Healthcare     BIIB           11.080848    752603.571429
 Healthcare     ABBV            8.569739   4826476.785714
 Healthcare      CVS            7.779541   3637359.821429
 Healthcare      LLY            7.440416       1768306.25
```

```
Healthcare     UNH            7.253478   1778942.857143
Healthcare     PFE            6.712639  21327650.892857
Healthcare     ABT            6.070936   3254866.964286
Healthcare     BMY            5.935182   6440792.857143
Healthcare     MRK            5.166594   8697586.607143,
            Tickers  Standard Deviation      Volume
Sectors
Real Estate     SPG            13.402588  1387918.75,
            Tickers  Standard Deviation          Volume
Sectors
Industrials      BA            13.633314  6776169.642857
Industrials     CAT             8.394303  2384585.714286
Industrials     UNP             7.524285  2148769.642857
Industrials     LMT             6.520709   787491.964286,
          Tickers  Standard Deviation          Volume
Sectors
Utilities      SO             6.14726  2736672.321429
Utilities     NEE             5.72065  4644516.964286,
                        Tickers  Standard Deviation         Volume
Sectors
Communication Services    GOOG            7.670060  723633.035714
Communication Services   CMCSA            7.578767    10583018.75
Communication Services       T            5.640447    24657718.75,
                    Tickers  Standard Deviation          Volume
Sectors
Consumer Defensive     TGT            8.669339  2036626.785714
Consumer Defensive      PM            7.570634  2618207.142857
Consumer Defensive      MO            6.760152  4468792.857143
Consumer Defensive      KO            5.638519  9514454.464286
Consumer Defensive    COST            5.091330  1203228.571429
Consumer Defensive     PEP            5.026444  2789961.607143
Consumer Defensive      CL            4.817024  2655066.071429
Consumer Defensive      PG            4.376677  4636135.714286]
```

[35]:

```python
def get_correlations(sector, sector_list):

    # creating temporary lists to transform later
    returned_list = [sector]
    correlation_list = []

    # creating an empty dataframe for now
    sector_df = pd.DataFrame()

    # filling up the sector monthly returns
    for i in range (0, len(sector)):

        # getting ticker name, ticker history, weighted close price
```

```
        sector_ticker = yf.Ticker(sector.iloc[i, 0])
        sector_history = sector_ticker.history(start='2018-01-01',␣
↪end='2021-11-19')
        sector_close_price = sector_history['Close']

        # converting to monthly data
        sector_close_price.index = pd.to_datetime(sector_close_price.index)
        sector_monthly_close_price = sector_close_price.
↪groupby(sector_close_price.index.to_period('m')).head(1)
        sector_df['Monthly Close Price of ' + sector.iloc[i,0]] =␣
↪sector_monthly_close_price

    # calculating value of sector (as if it were a portfolio), monthly returns␣
↪and standard deviation
    sector_df['Value of Sector'] = sector_df.sum(axis=1)
    sector_df['Monthly Returns'] = sector_df['Value of Sector'].pct_change()*100
    sector_df = sector_df['Monthly Returns']

    # getting the correlations of the rest of the sectors
    for j in range (0, len(sector_list)):

        # temporary dataframe to store values
        temp = pd.DataFrame()
        correlation = pd.DataFrame()

        # dataframe with each stock in a specific sector
        init_sector = sector_list[j]

        # for-loop for each stock in a sector
        for k in range (0, len(init_sector)):
            # getting ticker name, ticker history, weighted close price
            ticker = yf.Ticker(init_sector.iloc[k, 0])
            history = ticker.history(start='2018-01-01', end='2021-11-19')
            close_price = history['Close']

            # converting to monthly data
            close_price.index = pd.to_datetime(close_price.index)
            monthly_close = close_price.groupby(close_price.index.
↪to_period('m')).head(1)

            temp['Monthly Close Price of ' + init_sector.iloc[k,0]] =␣
↪monthly_close

        # calculating value of sector (as if it were a portfolio), monthly␣
↪returns and standard deviation
        temp['Value of Sector'] =  temp.sum(axis=1)
```

```
        temp['Monthly Returns'] = temp['Value of Sector'].pct_change()*100
        temp = temp['Monthly Returns']

        # concatenating the sector dataframe along with the dataframe of the␣
↪other sector
        combined = pd.concat([sector_df, temp], join='inner', axis=1)

        # calculating the correlation and extracting the correlation
        correlation = combined.corr().iloc[0, 1]

        # appending the correlation, along with the sector name to a list
        correlation_list.append([init_sector.index[0], correlation,␣
↪sector_list[j]])

    # sorting the list with the sectors and correlation information from␣
↪greatest to least
    correlation_list.sort(key=lambda x: x[1], reverse=True)

    # appending the sectors with the highest correlations to a separate list
    for l in range (0, len(correlation_list)):
        correlation_sector = correlation_list[l]
        returned_list.append(correlation_sector[2])

    # returning the data
    return returned_list
```

[36]:
```
# list with sectors in an descending correlative order
list_of_corr = (get_correlations(high_deviation_sector, new_filtered))

# displaying the list
list_of_corr
```

[36]:
```
[        Tickers  Standard Deviation           Volume
 Sectors
 Energy      OXY           19.543815  11707057.142857
 Energy      SLB           15.023794   7528641.964286
 Energy      COP           12.924563   6067660.714286
 Energy      KMI            8.874310   9776673.214286,
             Tickers  Standard Deviation      Volume
 Sectors
 Real Estate     SPG           13.402588  1387918.75,
                     Tickers  Standard Deviation           Volume
 Sectors
 Financial Services     COF           12.107918   1965058.035714
 Financial Services     AIG           12.029141   2983665.178571
 Financial Services       C           11.555252  12883508.928571
 Financial Services      MS            9.995934   5997000.892857
```

```
Financial Services     BAC           9.501078  33489260.714286
Financial Services    PYPL           9.442428   4678679.464286
Financial Services     AXP           8.920671   2532703.571429
Financial Services     USB           8.331631   3711789.285714
Financial Services     JPM           8.063898   7968159.821429
Financial Services     BLK           7.788556        362068.75
Financial Services      BK           7.329313   3396391.964286
Financial Services      TD           7.024688       1057731.25,
            Tickers  Standard Deviation          Volume
Sectors
Industrials      BA           13.633314  6776169.642857
Industrials     CAT            8.394303  2384585.714286
Industrials     UNP            7.524285  2148769.642857
Industrials     LMT            6.520709   787491.964286,
                       Tickers  Standard Deviation         Volume
Sectors
Communication Services    GOOG            7.670060  723633.035714
Communication Services   CMCSA            7.578767    10583018.75
Communication Services       T            5.640447    24657718.75,
           Tickers  Standard Deviation          Volume
Sectors
Technology    SHOP           14.632376   691973.214286
Technology    QCOM           12.599123  4954920.535714
Technology    AAPL           10.091369  55696846.428571
Technology    CSCO            7.768640  10937365.178571
Technology     ACN            6.994099   1248614.285714
Technology     TXN            6.685049        2425787.5
Technology    MSFT            6.305217  15980571.428571
Technology    ORCL            5.821712   7671951.785714,
           Tickers  Standard Deviation          Volume
Sectors
Healthcare    BIIB           11.080848    752603.571429
Healthcare    ABBV            8.569739   4826476.785714
Healthcare     CVS            7.779541   3637359.821429
Healthcare     LLY            7.440416       1768306.25
Healthcare     UNH            7.253478   1778942.857143
Healthcare     PFE            6.712639  21327650.892857
Healthcare     ABT            6.070936   3254866.964286
Healthcare     BMY            5.935182   6440792.857143
Healthcare     MRK            5.166594   8697586.607143,
                   Tickers  Standard Deviation         Volume
Sectors
Consumer Defensive     TGT            8.669339  2036626.785714
Consumer Defensive      PM            7.570634  2618207.142857
Consumer Defensive      MO            6.760152  4468792.857143
Consumer Defensive      KO            5.638519  9514454.464286
Consumer Defensive    COST            5.091330  1203228.571429
```

```
Consumer Defensive     PEP            5.026444  2789961.607143
Consumer Defensive      CL            4.817024  2655066.071429
Consumer Defensive      PG            4.376677  4636135.714286,
          Tickers  Standard Deviation          Volume
Sectors
Utilities      SO             6.14726  2736672.321429
Utilities     NEE             5.72065  4644516.964286]
```

[37]:

```
# Correlation Matrix For Data For Discussion

# getting the monthly returns of each sector
def find_returns(df):

    # sectors without any tickers inside of them
    if (len(df) == 0):
        return None

    # sectors with tickers inside of them
    else:

        # creating a temporary dataframe
        init_frame = pd.DataFrame(columns=['Close Prices'])

        # getting the ticker, ticker history and close price
        init_ticker = yf.Ticker(df.iloc[0,0])
        init_hist = init_ticker.history(start="2018-01-01", end="2021-11-19")
        init_close = init_hist['Close']

        # converting the daily data to monthly data
        init_close.index = pd.to_datetime(init_close.index)
        monthly_init_close = init_close.groupby(init_close.index.
↪to_period('m')).head(1)
        init_frame['Close Prices'] = monthly_init_close

        # if there is only one stock in the sector
        if (len(df) == 1):
            init_frame['Monthly Returns'] = init_frame['Close Prices'].
↪pct_change()*100
            return init_frame['Monthly Returns']

        else:
            # looping through the sectors to get the monthly returns
            for i in range (1, len(df)):

                # getting the ticker, ticker history and close price history
                ticker = yf.Ticker(df.iloc[i, 0])
```

```
                ticker_hist = ticker.history(start="2018-01-01",␣
↪end="2021-11-19")
                ticker_close = ticker_hist['Close']

                # converting the daily data to monthly data
                ticker_close.index = pd.to_datetime(ticker_close.index)
                monthly_close = ticker_close.groupby(ticker_close.index.
↪to_period('m')).head(1)

                # adding the close prices of each stock
                init_frame['Close Prices'] = init_frame['Close Prices'] +␣
↪monthly_close

                # calculating the monthly returns
                init_frame['Monthly Returns'] = init_frame['Close Prices'].
↪pct_change()*100

            # returning the monthly returns
            return init_frame['Monthly Returns']

    return 1
```

[38]:

```
# Outputting correlation matrix for correlation between sectors
correlation = pd.DataFrame()
correlation['Energy Monthly Returns (%)'] = find_returns(energy_list)
correlation['Financial Services Monthly Returns (%)'] =␣
↪find_returns(financial_list)
correlation['Technology Monthly Returns (%)'] = find_returns(tech_list)
correlation['Healthcare Monthly Returns (%)'] = find_returns(healthcare_list)
correlation['Real Estate Monthly Returns (%)'] = find_returns(estate_list)
correlation['Industrials Monthly Returns (%)'] = find_returns(industry_list)
correlation['Utilities Monthly Returns (%)'] = find_returns(utilities_list)
correlation['Communication Services Monthly Returns (%)'] =␣
↪find_returns(communication_list)
correlation['Materials Monthly Returns (%)'] = find_returns(materials_list)
correlation['Consumer Defensive Monthly Returns (%)'] =␣
↪find_returns(consumer_list)
correlation['Consumer Cyclical Monthly Returns (%)'] =␣
↪find_returns(cyclical_list)

print(correlation.corr())
```

```
                                            Energy Monthly Returns (%)  \
Energy Monthly Returns (%)                                    1.000000
Financial Services Monthly Returns (%)                        0.795653
Technology Monthly Returns (%)                                0.580785
Healthcare Monthly Returns (%)                                0.479978
```

```
Real Estate Monthly Returns (%)                              0.803352
Industrials Monthly Returns (%)                              0.725199
Utilities Monthly Returns (%)                                0.233866
Communication Services Monthly Returns (%)                   0.655360
Consumer Defensive Monthly Returns (%)                       0.375178
Consumer Cyclical Monthly Returns (%)                        0.362464

                                            Financial Services Monthly Returns
(%)  \
Energy Monthly Returns (%)
0.795653
Financial Services Monthly Returns (%)
1.000000
Technology Monthly Returns (%)
0.742083
Healthcare Monthly Returns (%)
0.587903
Real Estate Monthly Returns (%)
0.738083
Industrials Monthly Returns (%)
0.819542
Utilities Monthly Returns (%)
0.468138
Communication Services Monthly Returns (%)
0.808148
Consumer Defensive Monthly Returns (%)
0.608093
Consumer Cyclical Monthly Returns (%)
0.583099

                                            Technology Monthly Returns (%)  \
Energy Monthly Returns (%)                                        0.580785
Financial Services Monthly Returns (%)                            0.742083
Technology Monthly Returns (%)                                    1.000000
Healthcare Monthly Returns (%)                                    0.505632
Real Estate Monthly Returns (%)                                   0.588444
Industrials Monthly Returns (%)                                   0.625862
Utilities Monthly Returns (%)                                     0.308772
Communication Services Monthly Returns (%)                        0.654443
Consumer Defensive Monthly Returns (%)                            0.538910
Consumer Cyclical Monthly Returns (%)                             0.744734

                                            Healthcare Monthly Returns (%)  \
Energy Monthly Returns (%)                                        0.479978
Financial Services Monthly Returns (%)                            0.587903
Technology Monthly Returns (%)                                    0.505632
Healthcare Monthly Returns (%)                                    1.000000
Real Estate Monthly Returns (%)                                   0.422950
```

```
Industrials Monthly Returns (%)                               0.520201
Utilities Monthly Returns (%)                                 0.286874
Communication Services Monthly Returns (%)                    0.574952
Consumer Defensive Monthly Returns (%)                        0.461015
Consumer Cyclical Monthly Returns (%)                         0.471405

                                            Real Estate Monthly Returns (%)  \
Energy Monthly Returns (%)                                         0.803352
Financial Services Monthly Returns (%)                             0.738083
Technology Monthly Returns (%)                                     0.588444
Healthcare Monthly Returns (%)                                     0.422950
Real Estate Monthly Returns (%)                                    1.000000
Industrials Monthly Returns (%)                                    0.643301
Utilities Monthly Returns (%)                                      0.404456
Communication Services Monthly Returns (%)                         0.646633
Consumer Defensive Monthly Returns (%)                             0.508096
Consumer Cyclical Monthly Returns (%)                              0.327378

                                            Industrials Monthly Returns (%)  \
Energy Monthly Returns (%)                                         0.725199
Financial Services Monthly Returns (%)                             0.819542
Technology Monthly Returns (%)                                     0.625862
Healthcare Monthly Returns (%)                                     0.520201
Real Estate Monthly Returns (%)                                    0.643301
Industrials Monthly Returns (%)                                    1.000000
Utilities Monthly Returns (%)                                      0.370225
Communication Services Monthly Returns (%)                         0.653109
Consumer Defensive Monthly Returns (%)                             0.610577
Consumer Cyclical Monthly Returns (%)                              0.463224

                                            Utilities Monthly Returns (%)  \
Energy Monthly Returns (%)                                       0.233866
Financial Services Monthly Returns (%)                           0.468138
Technology Monthly Returns (%)                                   0.308772
Healthcare Monthly Returns (%)                                   0.286874
Real Estate Monthly Returns (%)                                  0.404456
Industrials Monthly Returns (%)                                  0.370225
Utilities Monthly Returns (%)                                    1.000000
Communication Services Monthly Returns (%)                       0.487429
Consumer Defensive Monthly Returns (%)                           0.560769
Consumer Cyclical Monthly Returns (%)                            0.159902

                                            Communication Services Monthly
Returns (%)  \
Energy Monthly Returns (%)
0.655360
Financial Services Monthly Returns (%)
0.808148
```

```
Technology Monthly Returns (%)
0.654443
Healthcare Monthly Returns (%)
0.574952
Real Estate Monthly Returns (%)
0.646633
Industrials Monthly Returns (%)
0.653109
Utilities Monthly Returns (%)
0.487429
Communication Services Monthly Returns (%)
1.000000
Consumer Defensive Monthly Returns (%)
0.576964
Consumer Cyclical Monthly Returns (%)
0.574097

                                            Consumer Defensive Monthly Returns
(%)  \
Energy Monthly Returns (%)
0.375178
Financial Services Monthly Returns (%)
0.608093
Technology Monthly Returns (%)
0.538910
Healthcare Monthly Returns (%)
0.461015
Real Estate Monthly Returns (%)
0.508096
Industrials Monthly Returns (%)
0.610577
Utilities Monthly Returns (%)
0.560769
Communication Services Monthly Returns (%)
0.576964
Consumer Defensive Monthly Returns (%)
1.000000
Consumer Cyclical Monthly Returns (%)
0.411721

                                            Consumer Cyclical Monthly Returns
(%)
Energy Monthly Returns (%)
0.362464
Financial Services Monthly Returns (%)
0.583099
Technology Monthly Returns (%)
0.744734
```

```
Healthcare Monthly Returns (%)
0.471405
Real Estate Monthly Returns (%)
0.327378
Industrials Monthly Returns (%)
0.463224
Utilities Monthly Returns (%)
0.159902
Communication Services Monthly Returns (%)
0.574097
Consumer Defensive Monthly Returns (%)
0.411721
Consumer Cyclical Monthly Returns (%)
1.000000
```

After finding the standard deviation of each sector, we decided to use the sector with the highest standard deviation as a foundation for our portfolio, then built the rest of the portfolio around that sector. To elaborate, we first included all the stocks from the sector with the highest standard deviation in the portfolio, as it should be the sector with the riskiest stocks. Furthermore, since all the stocks are from the same sector, they should be fairly positively correlated. As a result, we will have a group of risky stocks that generally move in the same direction, so the risk of the overall portfolio will increase. Then, we found the correlation of all the sectors with each other, as shown above. We sorted the rest of the sectors by their correlation with the riskiest sector, from highest positive correlation to negative correlation.

Next, we added stocks from the most positively correlated sectors from the sorted list to the portfolio until we had 10 stocks in the portfolio. The result can be seen from the ticker_list dataframe below, where we include all the stocks from a sector before moving on to the next sector. This limits the amount of sectors we have in our portfolio, and since all the sectors are as positively correlated as possible, the amount of inter-industry diversification is limited as well. To reiterate, we tried to include the least amount of sectors in our portfolio as possible by including all the stocks from the riskiest sectors. As a result, our portfolio becomes more prone to risk that is specific to the industries that we have in our portfolio. Moreover, we selected the sectors that have the highest positive correlation with the riskiest sector, so the stocks in the portfolio will generally move in the same direction, further increasing risk. We decided to only have 10 stocks in our portfolio as we wanted to have the least amount of stocks as possible, to limit the amount of diversification. With less stocks in our portfolio, each stock will have a greater influence on the performance of the overall portfolio, thus increasing risk. In the case that we could not include an entire sector in our portfolio due to the limit of 10 stocks, the stocks with the highest standard deviation were added to our portfolio, maximizing the risk of the portfolio.

[39]:
```
ticker_list = pd.concat(list_of_corr)
```

[40]:
```
# Selecting first 10 stocks of list
ticker_list = ticker_list[:10]
ticker_list
```

[40]:

```
                      Tickers  Standard Deviation          Volume
Sectors
Energy                    OXY           19.543815  11707057.142857
Energy                    SLB           15.023794   7528641.964286
Energy                    COP           12.924563   6067660.714286
Energy                    KMI            8.874310   9776673.214286
Real Estate               SPG           13.402588       1387918.75
Financial Services        COF           12.107918   1965058.035714
Financial Services        AIG           12.029141   2983665.178571
Financial Services          C           11.555252  12883508.928571
Financial Services         MS            9.995934   5997000.892857
Financial Services        BAC            9.501078  33489260.714286
```

[41]:

```python
# Function to get percentage returns of a monthly prices of a stock
def get_returns (ticker):
    stock = yf.Ticker(ticker)
    start_date = '2018-01-01'
    end_date = '2021-11-19'
    history = stock.history(start=start_date, end=end_date)
    prices = pd.DataFrame({ticker: history['Close']})
    prices = prices.resample('MS').ffill()
    prices = prices.pct_change()
    return prices
```

[42]:

```python
return_list = get_returns(ticker_list.iloc[0,0])
```

[43]:

```python
# Function to get percentage returns of all 10 stocks in the portfolio
i = 1
for i in range (len(ticker_list)):
    ticker = ticker_list.iloc[i,0]
    add_returns = get_returns (ticker)
    return_list = pd.concat([return_list, add_returns], join = 'inner', axis =␣
 ↪1)
```

[44]:

```python
return_list = return_list.iloc[: , 1:]
```

[45]:

```python
return_list
```

[45]:

```
                 OXY       SLB       COP       KMI       SPG       COF  \
Date
2018-01-01       NaN       NaN       NaN       NaN       NaN       NaN
2018-02-01       NaN       NaN       NaN       NaN       NaN       NaN
2018-03-01 -0.137582 -0.130178 -0.087279 -0.102436 -0.017281 -0.074366
2018-04-01  0.001622 -0.006746  0.100408 -0.070944 -0.003808 -0.007149
2018-05-01  0.178879  0.055882  0.108282  0.077025  0.034921 -0.064183
2018-06-01  0.111256  0.008187  0.043553  0.054931  0.019491  0.061457
2018-07-01 -0.007852 -0.020900  0.019476  0.045562  0.058396 -0.030284
```

```
2018-08-01 -0.012428 -0.005520  0.035692  0.003287  0.044421  0.035800
2018-09-01 -0.033519 -0.052505  0.022560  0.009698  0.041463  0.045337
2018-10-01  0.051389 -0.017076  0.087975  0.027119 -0.034912 -0.041780
2018-11-01 -0.177794 -0.161227 -0.125388 -0.044496  0.028306 -0.059505
2018-12-01  0.028090 -0.126984 -0.048865 -0.005245  0.033325  0.008712
2019-01-01 -0.116303 -0.191266 -0.057872 -0.099004 -0.095320 -0.157114
2019-02-01  0.108504  0.235034  0.101524  0.206476  0.066790  0.069983
2019-03-01 -0.007202  0.025878  0.008197  0.075749 -0.009309  0.047090
2019-04-01  0.006464 -0.009515 -0.017989  0.015198  0.041921  0.002611
2019-05-01 -0.144388 -0.075737 -0.074161 -0.010224 -0.028317  0.095881
2019-06-01 -0.134134 -0.161469 -0.054513  0.018377 -0.077416 -0.068346
2019-07-01  0.016366  0.149665  0.055800  0.046616 -0.021284  0.071853
2019-08-01  0.068100 -0.020600 -0.050621  0.006780 -0.007312 -0.008040
2019-09-01 -0.182246 -0.157881 -0.112585 -0.024073 -0.040990 -0.047085
2019-10-01  0.024473  0.024115  0.056918  0.000987  0.022962  0.028285
2019-11-01 -0.033813  0.053211  0.044103  0.023030  0.011420  0.069384
2019-12-01 -0.087964  0.051104  0.048819 -0.043415 -0.005219  0.054290
2020-01-01  0.090532  0.125981  0.084918  0.079551 -0.014880  0.028997
2020-02-01 -0.036156 -0.166418 -0.086114 -0.002529 -0.106136 -0.030221
2020-03-01 -0.175730 -0.179643 -0.179493 -0.081457 -0.061467 -0.112201
2020-04-01 -0.662020 -0.535253 -0.388269 -0.335942 -0.617810 -0.493768
2020-05-01  0.418994  0.250993  0.321404  0.163853  0.343537  0.378245
2020-06-01 -0.093832  0.170159  0.119671  0.083104 -0.025316  0.127748
2020-07-01  0.261405 -0.031958 -0.061074 -0.054534  0.133279 -0.120162
2020-08-01 -0.095922  0.023702 -0.072866 -0.036633 -0.088835  0.051071
2020-09-01 -0.207116  0.033810 -0.006151 -0.016312  0.077787  0.076616
2020-10-01 -0.223599 -0.194310 -0.127287 -0.117520 -0.009970  0.063430
2020-11-01 -0.056818 -0.004664 -0.106632 -0.006103 -0.038314  0.002057
2020-12-01  0.657174  0.418839  0.372118  0.184874  0.353128  0.228984
2021-01-01  0.144683  0.036070  0.018335 -0.030497  0.019239  0.102007
2021-02-01  0.177932  0.015117  0.018005  0.044300  0.089822  0.040567
2021-03-01  0.355566  0.302109  0.304180  0.072753  0.225737  0.208948
2021-04-01 -0.009074 -0.021588  0.026801  0.119681  0.011236  0.047204
2021-05-01 -0.073776 -0.037367 -0.053314  0.028391  0.068644  0.148713
2021-06-01  0.122634  0.222252  0.148288  0.085631  0.102267  0.118035
2021-07-01  0.154593  0.004251  0.079114 -0.004322 -0.009116 -0.054737
2021-08-01 -0.205721 -0.128213 -0.101644 -0.042530 -0.038163  0.028953
2021-09-01 -0.039081 -0.025174 -0.025152 -0.070196  0.073427  0.007283
2021-10-01  0.242524  0.085061  0.282708  0.046411 -0.008610  0.030059
2021-11-01  0.117496  0.096838  0.070444  0.024218  0.121827 -0.081242

                 AIG         C        MS       BAC
Date
2018-01-01       NaN       NaN       NaN       NaN
2018-02-01       NaN       NaN       NaN       NaN
2018-03-01 -0.119994 -0.066176 -0.051523 -0.027750
2018-04-01 -0.030758 -0.083627 -0.009727 -0.047332
```

```
2018-05-01  0.034730  0.011111 -0.035224 -0.001334
2018-06-01 -0.053632 -0.009548 -0.011581 -0.014353
2018-07-01  0.000803 -0.005351 -0.074399 -0.041157
2018-08-01  0.037156  0.074866  0.064908  0.108549
2018-09-01 -0.033097 -0.003350 -0.026903 -0.010240
2018-10-01  0.004410  0.009686 -0.045054 -0.036750
2018-11-01 -0.187641 -0.084805 -0.009106 -0.062057
2018-12-01  0.003015 -0.009024 -0.032687  0.021215
2019-01-01 -0.080946 -0.196481 -0.106781 -0.127546
2019-02-01  0.111900  0.231610  0.062228  0.151786
2019-03-01 -0.013464  0.012565  0.016260  0.038043
2019-04-01  0.025071 -0.001706  0.024235 -0.026271
2019-05-01  0.065470  0.087011  0.099699  0.060266
2019-06-01  0.089609 -0.105917 -0.144629 -0.120952
2019-07-01  0.060648  0.138214  0.080118  0.111991
2019-08-01  0.016159 -0.033786 -0.015591  0.002379
2019-09-01 -0.048802 -0.051444 -0.033543 -0.067141
2019-10-01  0.050642  0.059052 -0.002651  0.040620
2019-11-01 -0.011219  0.091237  0.152402  0.118143
2019-12-01 -0.020461  0.017335  0.045426  0.047799
2020-01-01 -0.019111  0.063498  0.033145  0.062794
2020-02-01 -0.020846 -0.062419  0.029010 -0.067859
2020-03-01 -0.161162 -0.147158 -0.138347 -0.131892
2020-04-01 -0.480959 -0.393161 -0.297801 -0.301890
2020-05-01  0.105969  0.194577  0.225106  0.167425
2020-06-01  0.278243  0.086336  0.164062  0.066291
2020-07-01 -0.021849  0.018200  0.065101 -0.048264
2020-08-01  0.086545  0.003306  0.033827  0.069648
2020-09-01 -0.093031  0.023795  0.075696  0.033360
2020-10-01 -0.038420 -0.151563 -0.101179 -0.056092
2020-11-01  0.136003 -0.034683  0.026384 -0.016598
2020-12-01  0.248333  0.339208  0.314226  0.210548
2021-01-01 -0.029062  0.111592  0.159970  0.063050
2021-02-01 -0.011622 -0.044306 -0.007472 -0.011547
2021-03-01  0.210850  0.190142  0.169795  0.194593
2021-04-01  0.030422  0.051769 -0.011875  0.108861
2021-05-01  0.044631 -0.019203  0.059840  0.026336
2021-06-01  0.105263  0.119596  0.115809  0.058969
2021-07-01 -0.093020 -0.109704 -0.000977 -0.028079
2021-08-01 -0.019059 -0.040629  0.050690 -0.076553
2021-09-01  0.152693  0.054570  0.086789  0.073775
2021-10-01  0.022501 -0.001823 -0.050427  0.051245
2021-11-01  0.084895 -0.014969  0.057240  0.110724
```

[46]:
```
# Creating correlation matrix to decide on which stocks to invest the most␣
↪money in
corr = return_list.corr()
```

```
corr
```

[46]:

	OXY	SLB	COP	KMI	SPG	COF	AIG
OXY	1.000000	0.823128	0.862662	0.744357	0.823920	0.626659	0.624065
SLB	0.823128	1.000000	0.899146	0.838098	0.788567	0.783352	0.778967
COP	0.862662	0.899146	1.000000	0.778303	0.753066	0.718913	0.673343
KMI	0.744357	0.838098	0.778303	1.000000	0.730553	0.741465	0.729332
SPG	0.823920	0.788567	0.753066	0.730553	1.000000	0.800131	0.682680
COF	0.626659	0.783352	0.718913	0.741465	0.800131	1.000000	0.731447
AIG	0.624065	0.778967	0.673343	0.729332	0.682680	0.731447	1.000000
C	0.734900	0.901904	0.771989	0.819123	0.772465	0.814035	0.770484
MS	0.661527	0.820004	0.674004	0.632935	0.750672	0.813787	0.710326
BAC	0.689449	0.883079	0.770796	0.759636	0.746896	0.812578	0.752120

	C	MS	BAC
OXY	0.734900	0.661527	0.689449
SLB	0.901904	0.820004	0.883079
COP	0.771989	0.674004	0.770796
KMI	0.819123	0.632935	0.759636
SPG	0.772465	0.750672	0.746896
COF	0.814035	0.813787	0.812578
AIG	0.770484	0.710326	0.752120
C	1.000000	0.876075	0.917079
MS	0.876075	1.000000	0.839604
BAC	0.917079	0.839604	1.000000

[47]:

```
# Getting the stock that is the most positively correlated to the stock with␣
↪the highest standard deviation
highest_corr = pd.DataFrame({'test':corr[corr.columns[0]].nlargest(2)})
highest_corr
```

[47]:

	test
OXY	1.000000
COP	0.862662

After deciding on the 10 stocks for our portfolio, we needed to decide on how much of the portfolio to allocate to each stock. In order to create the riskiest portfolio, we needed to invest most of our money into the least amount of stocks as possible. To accomplish this, we invested 35 percent of the portfolio in the stock from the riskiest sector with the highest standard deviation. As mentioned earlier, standard deviation is a direct measure of risk, so the stock with the highest standard deviation should be the riskiest. Then, we invested 25 percent in the stock that is the most positively correlated with the stock with the highest standard deviation, as shown above. By doing this, we would invest 25 percent of our money in the stock that is the most directly related to riskiest stock. We invested 25 percent of our money in this stock as it was the most we could, since we needed to invest at least 5000 dollars in each stock to meet the requirements. As a result, we have 60 percent of our portfolio allocated to the 2 riskiest stocks that are positively correlated to each other, and 5 percent of our portfolio in each of the 8 other stocks. By having 60 percent of our portfolio in 2 stocks, we allowed the returns of the portfolio to be primarily determined by 2 stocks. Hence, we greatly limited the amount of diversification by increasing exposure to the risk of the 2 stocks, which in turn, increases the risk of the portfolio. As for the 8 other stocks, if they are highly positively correlated with the first 2 stocks, then they will further increase the risk the portfolio. On the other hand, if they have a lower correlation with the first 2 stocks, it won't affect the risk of the portfolio by too much, as we only invested 5 percent in each of these stocks.

[48]:
```
# Function to produce values for FinalPortfolio dataframe
def stock_df (ticker, value, num):
    myhistory = yf.Ticker(ticker).history(start='2021-05-19', end='2021-11-30',␣
 ↪interval= '1d')
    data= {'Ticker': ticker,
           'Price': myhistory.loc['2021-11-26', 'Close'],
           'Shares': value/myhistory.loc['2021-11-26', 'Close'],
           'Value': value,
           'Weight': [value/1000]}
    info = pd.DataFrame(data,index=[num])
    return info

# Investing 35000 dollars in first stock for FinalPortfolio dataframe
stock1 = stock_df (highest_corr.index[0], 35000, 1)

# Investing 25000 dollars in second stock for FinalPortfolio dataframe
stock2 = stock_df (highest_corr.index[1], 25000, 2)
```

[49]:
```
# Removing first stock from ticker list
ticker_list = ticker_list[ticker_list.Tickers != highest_corr.index[0]]
```

[50]:
```
# Removing second stock from ticker list
ticker_list = ticker_list[ticker_list.Tickers != highest_corr.index[1]]
```

[51]:
```
# List of eight other stocks for FinalPortfolio dataframe
ticker_list
```

[51]:

Sectors	Tickers	Standard Deviation	Volume
Energy	SLB	15.023794	7528641.964286
Energy	KMI	8.874310	9776673.214286
Real Estate	SPG	13.402588	1387918.75
Financial Services	COF	12.107918	1965058.035714
Financial Services	AIG	12.029141	2983665.178571
Financial Services	C	11.555252	12883508.928571
Financial Services	MS	9.995934	5997000.892857
Financial Services	BAC	9.501078	33489260.714286

In conclusion, to create a risky portfolio, we made sure that we included all the stocks from the riskiest sector in our portfolio, then added the riskiest and most positively correlated stocks to the portfolio. As a result, all of the stocks in our portfolio are positively correlated, thus increasing the risk of the portfolio. We also included the least amount of industries in our portfolio as possible to limit inter-industry diversification, and only had 10 stocks in our portfolio to limit overall diversification. Finally, we invested as much money as possible in the two riskiest stocks, allowing those two stocks to have a powerful influence on the performance of the overall portfolio, further increasing risk.

[52]:
```
FinalPortfolio = stock1.append(stock2)

i = 0

# Loop to create FinalPortfolio dataframe and invest 5000 dollars in the other␣
↪8 stocks
for i in range (8):
    add_stock = stock_df(ticker_list.iloc[i,0], 5000, i+3)
    FinalPortfolio = FinalPortfolio.append(add_stock)

# Finding total portfolio value and weight
total = pd.DataFrame({'Ticker': 'N/A',
                      'Price': 'N/A',
                      'Shares': 'N/A',
                      'Value': sum(FinalPortfolio.Value),
                      'Weight': sum(FinalPortfolio['Weight'])},␣
↪index=['Totals'])
```

[53]:
```
# Adding totals to FinalPortfolio
FinalPortfolio = FinalPortfolio.append(total)
```

[54]:
```
# Outputting FinalPortfolio
FinalPortfolio
```

[54]:

	Ticker	Price	Shares	Value	Weight
1	OXY	29.69035	1178.834217	35000	35.0
2	COP	71.282219	350.7186	25000	25.0
3	SLB	29.574791	169.062903	5000	5.0
4	KMI	16.26	307.503071	5000	5.0
5	SPG	158.798248	31.486493	5000	5.0
6	COF	149.160004	33.52105	5000	5.0
7	AIG	55.721863	89.731386	5000	5.0
8	C	65.5	76.335878	5000	5.0
9	MS	97.93	51.056877	5000	5.0
10	BAC	45.540802	109.791655	5000	5.0
Totals	N/A	N/A	N/A	100000	100.0

[55]:
```
# Adjusting FinalPortfolio to output as csv file
FinalPortfolio.drop(FinalPortfolio.tail(1).index,inplace=True)
```

[56]:
```
# Resetting index so that FinalPortfolio dataframe can be used for Stocks␣
↪dataframe
FinalPortfolio.reset_index(inplace=True)
```

[57]:
```python
# Creating Stocks dataframe to be outputted as csv file
Stocks = pd.concat([FinalPortfolio['index'], FinalPortfolio['Ticker'],
 ↪FinalPortfolio['Shares']], join='inner',axis=1)
Stocks.columns=['','Ticker','Shares']
```

[58]:
```python
# Exporting Stocks as csv file
Stocks.to_csv('Risky_Stock_Portfolio.csv', encoding='utf-8', index=False)
```