Team_10_Assignment

November 28, 2022

[1]:
```
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 math
import matplotlib.pyplot as plt
from datetime import datetime
```

0.1 Group Assignment

0.1.1 Team Number: 10

0.1.2 Team Member Names: Arteen, Avi, Momina

0.1.3 Team Strategy Chosen: Safe

1 1. Reading in the CSV file and filtering

The code in the following section reads in the appropriate CSV file and stores the tickers in a dataframe. Subsequent dataframes are created to store the hist and .info attributes of each ticker for easy access later on. The dataframe is then reformatted and filtered to adhere to the following assignment requirements: * The portfolio must only contain US listed stocks
* The portfolio may only include stocks that have an average monthly volume of at least 200,000 shares (calculated based on the time interval of January, 01 to October, 31, 2022)

[2]:
```
df = pd.read_csv('Tickers.csv')
print(df.head())

# Since the first ticker in the file is in the first row, it reads as the column
# name in the DF, so this code is to move it into the DF and replaces the column
missing = df.columns[0]
rest = df.rename(columns={missing:"Tickers"})
all_tickers = pd.DataFrame(data=[missing], columns=["Tickers"])
all_tickers = all_tickers.append(rest, ignore_index=True)

# NEW CODE
```

```
all_tickers.drop_duplicates(subset=None, inplace=True)

# NEW CODE END

all_tickers.head()
```

```
    ACRV
0  asdfa
1   AAPL
2   ABBV
3    LOW
4   AUST
```

```
C:\Users\Arteen\AppData\Local\Temp\ipykernel_12704\573412557.py:9:
FutureWarning: The frame.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  all_tickers = all_tickers.append(rest, ignore_index=True)
```

[2]:

```
  Tickers
0    ACRV
1   asdfa
2    AAPL
3    ABBV
4     LOW
```

[3]:

```
# applymap applies the function in the brackets to all the elements in the DF
all_stocks = all_tickers.applymap(yf.Ticker)
all_stocks['Names'] = all_tickers.Tickers

all_stocks.head()
```

[3]:

```
                          Tickers  Names
0   yfinance.Ticker object <ACRV>   ACRV
1  yfinance.Ticker object <ASDFA>  asdfa
2   yfinance.Ticker object <AAPL>   AAPL
3   yfinance.Ticker object <ABBV>   ABBV
4    yfinance.Ticker object <LOW>    LOW
```

[4]:

```
# Start by defining variables (intervals and dates)
interval = "1d"
start = "2022-01-01"
end = "2022-11-01"

# Create a history dataframe which contains tickers
all_history = pd.DataFrame(data=all_tickers, columns=["Tickers", "History",␣
 ↪"History M"])
# Adds prices to the history dataframe
```

```
all_history["History"] = [tick.history(start=start, end=end, interval=interval)␣
 ↪for tick in all_stocks.Tickers]
all_history["History M"] = [tick.history(start=start, end=end, interval='1mo')␣
 ↪for tick in all_stocks.Tickers]

all_history.head()
```

```
- ACRV: Data doesn't exist for startDate = 1641013200, endDate = 1667275200
- ASDFA: No data found, symbol may be delisted
- INVALIDTIC: No data found, symbol may be delisted
- CELG: No data found, symbol may be delisted
- ACRV: Data doesn't exist for startDate = 1641013200, endDate = 1667275200
- ASDFA: No data found, symbol may be delisted
- INVALIDTIC: No data found, symbol may be delisted
- CELG: No data found, symbol may be delisted
```

[4]:
```
  Tickers                                            History  \
0    ACRV  Empty DataFrame
Columns: [Open, High, Low, Clo…
1   asdfa  Empty DataFrame
Columns: [Open, High, Low, Clo…
2    AAPL                        Open        High          Low…
3    ABBV                        Open        High          Low…
4     LOW                        Open        High          Low…

                                           History M
0  Empty DataFrame
Columns: [Open, High, Low, Clo…
1  Empty DataFrame
Columns: [Open, High, Low, Clo…
2                     Open        High          Low…
3                     Open        High          Low…
4                     Open        High          Low…
```

[5]:
```
new = pd.DataFrame(columns=['Tickers'])
tick_lst = []

for tick in all_history["Tickers"]:
    # Get the history of the current stock
    hist = all_history[all_history["Tickers"] == tick]['History M'].iloc[0]
    vol = hist.Volume.dropna()  # drop any nans
    # print(vol)

    x = 0  # Index when running through the history
    while x < len(vol):
        if x == len(vol) - 1: # If you've reached the end of the list, measure␣
 ↪against the last month
```

```
            # Get the number of business days in that month
            num_days = np.busday_count(vol.index[x].strftime("%Y-%m-%d"), end)
        else: # Measure against the next month
            # Get the number of business days in that month
            num_days = np.busday_count(vol.index[x].strftime("%Y-%m-%d"), vol.
 ↪index[x+1].strftime("%Y-%m-%d"))

        if num_days < 20:  # If the number of days is less than 20
            vol = vol.drop(vol.index[x])  # Drop the month
            # NOTE we don't increment the index. Since we're removing an␣
 ↪element from the DF, incrementing the index would
            # likely cause errors in the future
        else:
            # Increment in index in this case, since the original index doesn't␣
 ↪change
            x += 1

    # If the mean of the volume of stocks is greater than 200,000 and the value␣
 ↪is not NaN
    if vol.mean() >= 200000 and not math.isnan(vol.mean()):
        tick_lst.append(tick)  # Keep this value
    else:
        print(tick)

new['Tickers'] = tick_lst  # Set the DF
all_tickers = new  # Replace the old DF with the new one

# re-create all the previous dataframes around the new one
all_stocks = all_tickers.applymap(yf.Ticker)
all_stocks['Names'] = all_tickers.Tickers

all_history = pd.DataFrame(data=all_tickers, columns=["Tickers", "History"])
all_history["History"] = [tick.history(start=start, end=end, interval=interval)␣
 ↪for tick in all_stocks.Tickers]
```

```
ACRV
asdfa
INVALIDTIC
CELG
```

[6]:
```
# Gets the info for all the tickers (necessary for checking the market and for␣
 ↪diversification)

# IMPORTANT:
# yfinance is very slow, and getting info may take some time. PLEASE be patient.
# There are print statements to show that the code is still running and␣
 ↪functioning properly
```

```python
info = []  # Put all the info into a list
for tick in all_stocks.Tickers:
    print(tick)
    info.append(tick.info)

all_stocks["Info"] = info  # Store info locally so we don't have to call␣
↪yfinance again

all_stocks.head()
```

```
yfinance.Ticker object <AAPL>
yfinance.Ticker object <ABBV>
yfinance.Ticker object <LOW>
yfinance.Ticker object <AUST>
yfinance.Ticker object <HOOD>
yfinance.Ticker object <AMZN>
yfinance.Ticker object <AXP>
yfinance.Ticker object <BAC>
yfinance.Ticker object <BMBL>
yfinance.Ticker object <BK>
yfinance.Ticker object <HDFC.NS>
yfinance.Ticker object <SQ>
yfinance.Ticker object <VZ>
yfinance.Ticker object <CMCSA>
yfinance.Ticker object <SHOP>
yfinance.Ticker object <COST>
yfinance.Ticker object <CSCO>
yfinance.Ticker object <CVS>
yfinance.Ticker object <GM>
yfinance.Ticker object <GOOG>
yfinance.Ticker object <JPM>
yfinance.Ticker object <IBM>
yfinance.Ticker object <ORCL>
yfinance.Ticker object <OXY>
yfinance.Ticker object <DUOL>
yfinance.Ticker object <PEP>
yfinance.Ticker object <T.TO>
yfinance.Ticker object <SLB>
yfinance.Ticker object <SO>
yfinance.Ticker object <SPG>
yfinance.Ticker object <QQQ>
```

[6]:

```
                        Tickers Names  \
0  yfinance.Ticker object <AAPL>  AAPL
1  yfinance.Ticker object <ABBV>  ABBV
2   yfinance.Ticker object <LOW>   LOW
```

```
3  yfinance.Ticker object <AUST>  AUST
4  yfinance.Ticker object <HOOD>  HOOD

                                              Info
0  {'zip': '95014', 'sector': 'Technology', 'full…
1  {'zip': '60064-6400', 'sector': 'Healthcare', …
2  {'zip': '28117', 'sector': 'Consumer Cyclical'…
3  {'zip': 'V6C 0C3', 'sector': 'Basic Materials'…
4  {'zip': '94025', 'sector': 'Technology', 'full…
```

[7]:

```
# Create copies (just in case)
new = all_tickers.copy()
new_stocks = all_stocks.copy()
new_hist = all_history.copy()

# Loop through all the tickers
for tick in all_stocks['Names']:
    try:
        market = all_stocks[all_stocks['Names'] == tick]['Info'].
 ↪iloc[0]['market']  # the market the stock is listed in

        # NEW CODE

        quoteType = all_stocks[all_stocks['Names'] == tick]['Info'].
 ↪iloc[0]['quoteType'] # The type (equity, ETF, etc)
        if market != 'us_market' or quoteType != 'EQUITY':  # Since the stock␣
 ↪must be listed in the US
            print(tick)
            # Drop that stock from all the copies
            new = new.drop(index=new[new['Tickers'] == tick].index[0])
            new_stocks = new_stocks.drop(index=new_stocks[new_stocks['Names']␣
 ↪== tick].index[0])
            new_hist = new_hist.drop(index=new_hist[new_hist['Tickers'] ==␣
 ↪tick].index[0])
    # Sometimes we run into a keyerror, so automatically drop those that cause␣
 ↪the error
    except KeyError:
        print(tick)
        # Drop that stock from all the copies
        new = new.drop(index=new[new['Tickers'] == tick].index[0])
        new_stocks = new_stocks.drop(index=new_stocks[new_stocks['Names'] ==␣
 ↪tick].index[0])
        new_hist = new_hist.drop(index=new_hist[new_hist['Tickers'] == tick].
 ↪index[0])

    # NEW/MODIFIED CODE END
```

```
# Replace all the original functions with the filtered ones (new)
all_tickers = new
# Create a new index since the old one will have gaps
all_tickers['Index'] = list(range(0,len(all_tickers.Tickers)))
all_tickers.set_index('Index', inplace=True)

all_stocks = new_stocks
all_stocks['Index'] = list(range(0,len(all_stocks.Names)))
all_stocks.set_index('Index', inplace=True)

all_history = new_hist
all_history['Index'] = list(range(0,len(all_history.Tickers)))
all_history.set_index('Index', inplace=True)

all_tickers.head()
```

```
HDFC.NS
T.TO
QQQ
```

[7]:

```
      Tickers
Index
0        AAPL
1        ABBV
2         LOW
3        AUST
4        HOOD
```

2 2 a. Calculating Standard Deviation

Since we are aiming for the safest portfolio, our ultimate goal is to build a portfolio that generates a net return of zero dollars. For this reason, we must select stocks with the least volatility. So naturally, we have calculated the standard deviation for each ticker and utilised it as one of the key determining criteria of our portfolio generator. Specifically, standard deviation helps us weed out any exceptionally explosive stocks, while also allowing us to select stable, reliable stocks.

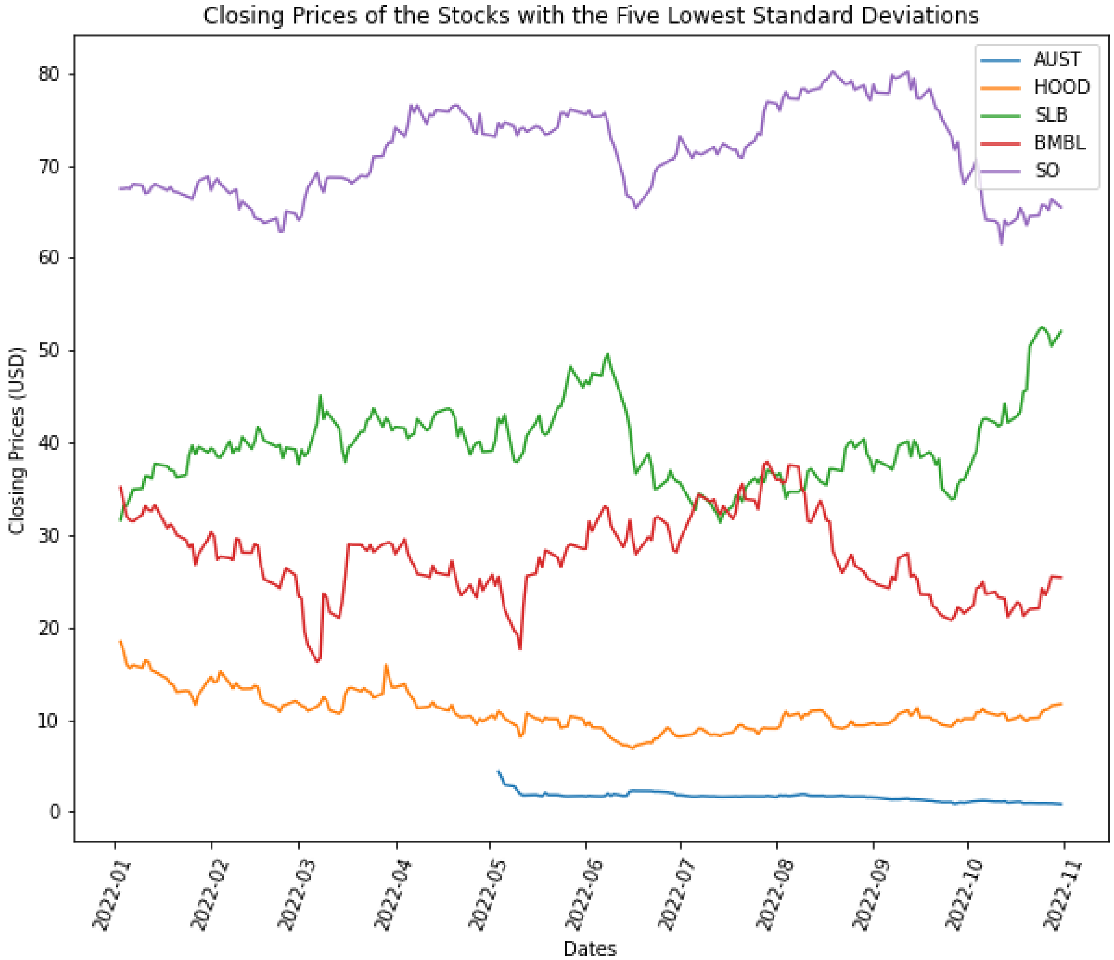
[8]:

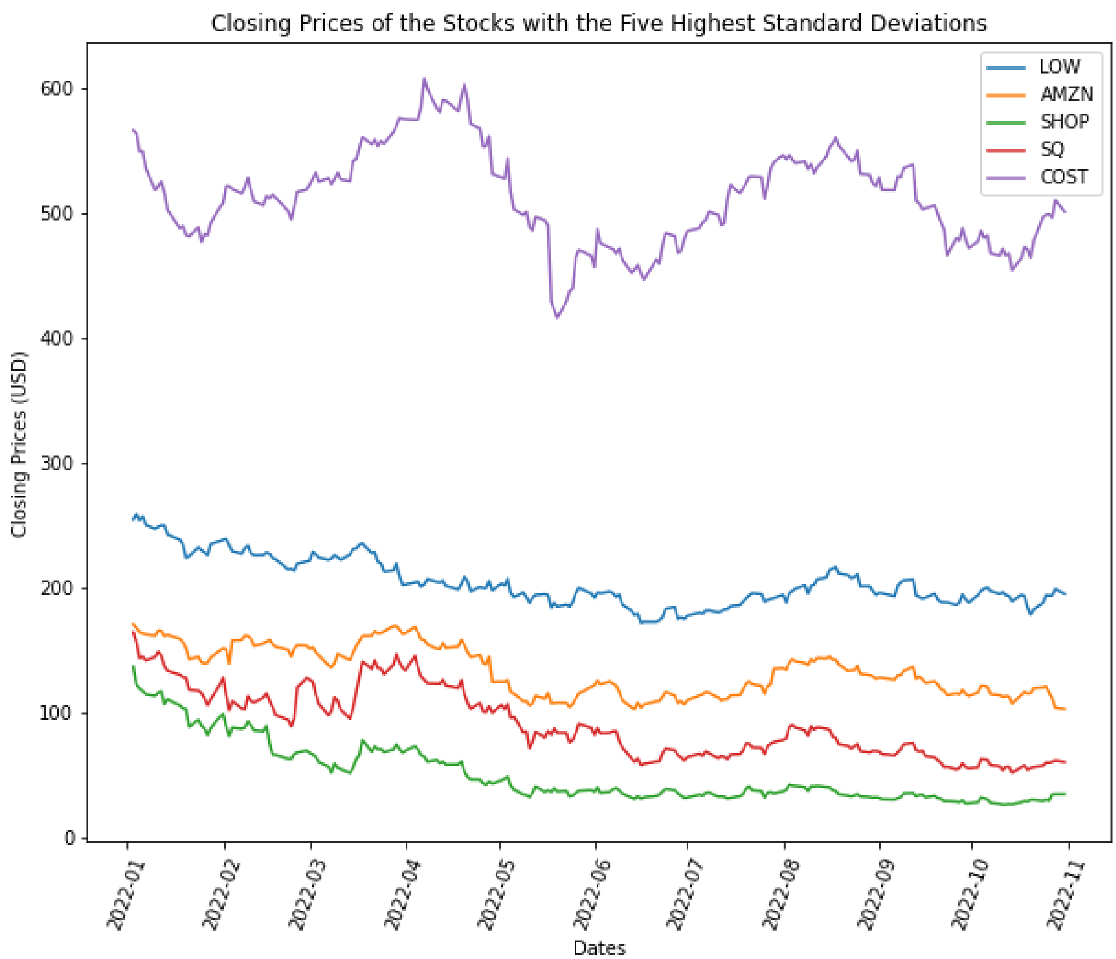
```
# Make a list containing (Ticker, STD) for all the tickers
all_std = [(all_history.Tickers[x], all_history.History[x]["Close"].std()) for␣
 ↪x in range(len(all_history["Tickers"]))]

# Sort by the second element in the tuple (STD, not Ticker Name)
all_std.sort(key=lambda x: x[1])

all_std[0:5]  # Show the top 5 lowest STD
```

[8]:
```
[('AUST', 0.5046745985606583),
 ('HOOD', 2.1343600828612574),
 ('SLB', 4.239894041012652),
 ('BMBL', 4.402119158572609),
 ('SO', 4.901778731508262)]
```

[9]:
```python
#This function is made to graph data from a list of (Ticker, data).
def graph_data(prices) :

    plt.figure(figsize=(10, 8))

    for p in prices :

        plt.plot(p[1].index, p[1], label=p[0])

    plt.xticks(rotation=70)
    plt.legend(loc='best')

#A list of (Ticker, Closing Price) of the stocks with the 5 lowest standard␣
 ↪deviations.
smallest_std_stock_prices = [(all_std[:5][x][0], all_stocks[all_stocks.Names ==␣
 ↪all_std[:5][x][0]].iloc[0].iloc[0].history(start=start, end=end)["Close"])␣
 ↪for x in range(len(all_std[:5]))]

#Graphing the closing prices for the stocks with the five lowest standard␣
 ↪deviations.
graph_data(smallest_std_stock_prices)

plt.title("Closing Prices of the Stocks with the Five Lowest Standard␣
 ↪Deviations")
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
#A list of (Ticker, Closing Price) of the stocks with the 5 lowest standard␣
 ↪deviations.
highest_std_stock_prices = [(all_std[len(all_std) - 5:][x][0],␣
 ↪all_stocks[all_stocks.Names == all_std[len(all_std) - 5:][x][0]].iloc[0].
 ↪iloc[0].history(start=start, end=end)["Close"]) for x in␣
 ↪range(len(all_std[len(all_std) - 5:]))]

#Graphing the closing prices for the stocks with the five lowest standard␣
 ↪deviations.
graph_data(highest_std_stock_prices)

plt.title("Closing Prices of the Stocks with the Five Highest Standard␣
 ↪Deviations")
```

```python
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
```





To further illustrate the importance of including standard deviation in our portfolio strategy, we have graphed the closing prices of the stocks with the 5 lowest, as well as the 5 highest, standard deviations.

Looking at the graphs, it is apparent that the closing prices of the stocks with lower standard deviations generally appear flatter (i.e., less volatile) than the stocks with higher standard deviations. These are exactly the type of stocks we want to favour in our portfolio, since steadier stocks won't fluctuate as much in value.

3 2 b. Calculating Expected Return

Given our goal of obtaining a net return of (near) \$0, the expected return of each individual stock is very relevant. To optimize the success of our portfolio, we would need to select stocks that have an expected return that is as close to 0 as possible.

There are a couple ways to calculate expected return. One of our options was to use the following formula:
> Expected return = (Return A x probability A) + (Return B x probability B) … + (Return i x

probability i)

However, accurately predicting all the different scenarios and their respective probabilities for unknown stocks is out of our scope, so this method wasn't feasible. Hence, we settled for a simpler approach:
> Expected return = [(Close Price at time 1) - (Close Price at time 2)] / (Close Price at time 1)

The timeframe we decided on was January 1, 2022 to November 1, 2022. This timeframe is recent enough so that the market conditions won't be that different, and it's also long enough that it gives us a more holistic view of the stock's trends.

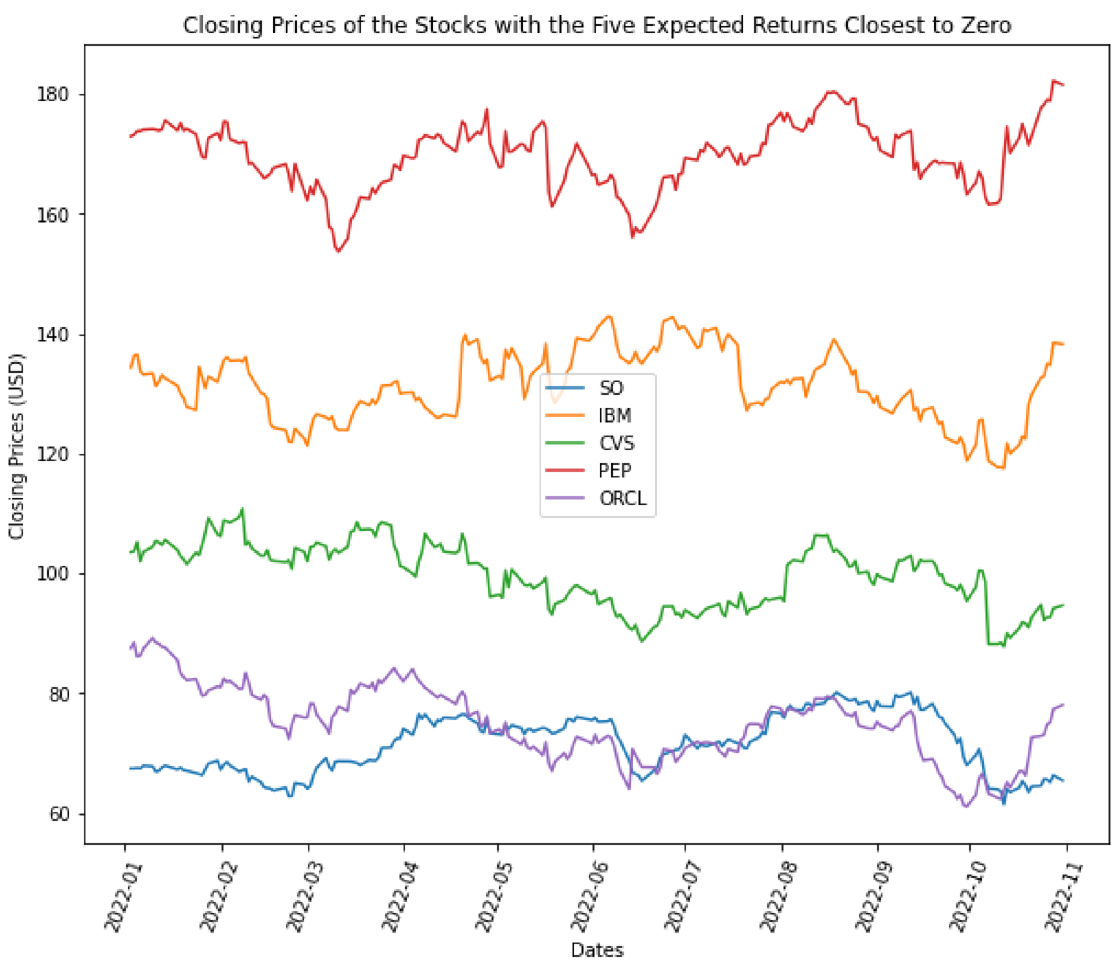
While some nuance is not being considered, the reasoning behind this strategy was as follows: if a stock has not increased or decreased in price significantly since January of this year, chances are it won't act up now.

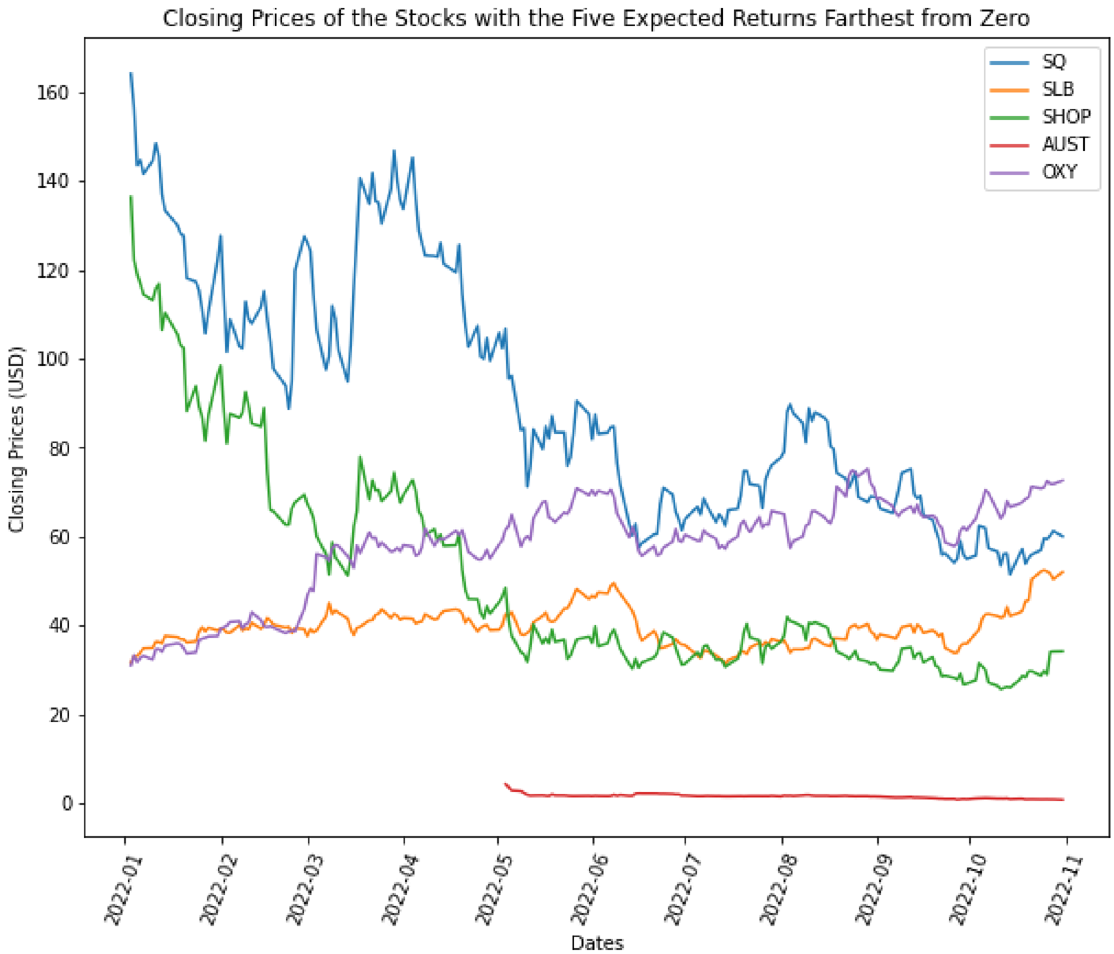
[10]:
```
expected_returns = [(all_history.Tickers[x], ((all_history.
 ↪History[x]['Close'][all_history.History[0]['Close'].index[-1]] - all_history.
 ↪History[x]['Close'][0])/all_history.History[x]['Close'][0])) for x in␣
 ↪range(len(all_history.Tickers))]
expected_returns.sort(key=lambda x:abs(x[1]))
expected_returns[0:5]
```

[10]:
```
[('SO', -0.011959520655878457),
 ('IBM', 0.05438291888816997),
 ('CVS', -0.07030338737137905),
 ('PEP', 0.07112043533836122),
 ('ORCL', -0.09642107267155238)]
```

[11]:
```
#A list of (Ticker, Closing Price) of the stocks with the 5 expected returns␣
 ↪closest to 0.
lowest_expected_return_stock_prices = [(expected_returns[:5][x][0],␣
 ↪all_stocks[all_stocks.Names == expected_returns[:5][x][0]].iloc[0].iloc[0].
 ↪history(start=start, end=end)["Close"]) for x in range(len(expected_returns[:
 ↪5]))]

#Graphing the closing prices for the stocks with the five expected returns␣
 ↪closest to 0.
graph_data(lowest_expected_return_stock_prices)

plt.title("Closing Prices of the Stocks with the Five Expected Returns Closest␣
 ↪to Zero")
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
#A list of (Ticker, Closing Price) of the stocks with the 5 expected returns␣
 ↪farthest from 0.
```

```
highest_expected_return_stock_prices = [(expected_returns[len(expected_returns)␣
 ↪- 5:][x][0], all_stocks[all_stocks.Names ==␣
 ↪expected_returns[len(expected_returns) - 5:][x][0]].iloc[0].iloc[0].
 ↪history(start=start, end=end)["Close"]) for x in␣
 ↪range(len(expected_returns[len(expected_returns) - 5:]))]

#Graphing the closing prices for the stocks with the five expected returns␣
 ↪farthest from 0.
graph_data(highest_expected_return_stock_prices)

plt.title("Closing Prices of the Stocks with the Five Expected Returns Farthest␣
 ↪from Zero")
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
```





We've created the above graphs to visualize the difference in the behaviour of stocks with high expected returns, compared to that of those with returns near \$0. We can concretely see that stocks with higher expected returns tend to have more fluctuations, meaning that their stock price is more volatile. Contrastingly, stocks with expected returns closer to \$0 tend to be less volatile, and their closing price remains more consistent. As a result, we gave companies with projected returns near \$0 greater priority than stocks with really high or really low expected returns.

4 2 c. Calculating Beta

While standard deviation determines the volatility of a fund according to the disparity of its returns over a period of time, beta compares the risk of a fund with the overall market's volatility. It's important to take into account a particular stock's volatility individually (through standard deviation), as well as the stock's volatility compared to the market – i.e., its beta value. Our code heavily favours stocks with low beta values, as this indicates that the stock is less volatile than the market, and will therefore not fluctuate as much.

[12]:
```python
#Calculating a list of containing (Ticker, daily % returns) for all tickers.
daily_returns = [(all_history.Tickers[x], all_history.History[x]["Close"].
 ↪pct_change()) for x in range(len(all_history.Tickers))]

#Getting the market returns and prices for the S&P 500
def get_market_returns():
    start = '2022-01-01'
    end = '2022-11-01'
    interval = '1d'
    market_index = '^GSPC'

    market_hist = yf.Ticker('^GSPC').history(start=start, end=end,␣
 ↪interval=interval)

    market_prices = market_hist['Close']

    market_returns = market_prices.pct_change().dropna()

    return (market_returns, market_prices)

#Calculating the daily returns in a list of (Ticker, Daily market returns).
daily_market_returns, market_prices = get_market_returns()

# Calculating both the market variances for daily returns and five day returns.
market_variance = daily_market_returns.var()

#Calculating the betas in a list of (Ticker, beta) for each daily return.
betas = [(all_history.Tickers[x], (pd.DataFrame({daily_returns[x][0] :␣
 ↪daily_returns[x][1],
                                                 '^GSPC' :␣
 ↪daily_market_returns}).cov()/market_variance).iat[0, 1]) for x in␣
 ↪range(len(all_history.Tickers)) if not math.isnan(all_history.
 ↪History[x]['Close'].std())]
betas.sort(key=lambda x: x[1])

betas[:5]
```

[12]:
```
[('ABBV', 0.34582605462546584),
 ('VZ', 0.3716061223824777),
 ('SO', 0.4227647238919992),
 ('IBM', 0.5078318372735184),
 ('PEP', 0.5126891943914723)]
```

[13]:

```
#Calculating the monthly returns of the stock with the lowest beta and the␣
↪stock with the second lowest beta.
low_beta_monthly_returns_1 = all_stocks[all_stocks.Names == betas[0][0]].
↪iloc[0].iloc[0].history(start=start, end=end, interval="1mo")["Close"].
↪pct_change().dropna()
low_beta_monthly_returns_2 = all_stocks[all_stocks.Names == betas[1][0]].
↪iloc[0].iloc[0].history(start=start, end=end, interval="1mo")["Close"].
↪pct_change().dropna()

#Creating a DataFrame to calculate the correlation between the stock with the␣
↪lowest beta and the stock with the second lowest beta.
correlation_df = pd.DataFrame({betas[1][0] : low_beta_monthly_returns_2,
                               betas[0][0] : low_beta_monthly_returns_1})

#Calculation the correlation.
correlation_df.corr()
```

[13]:

	VZ	ABBV
VZ	1.000000	0.478748
ABBV	0.478748	1.000000

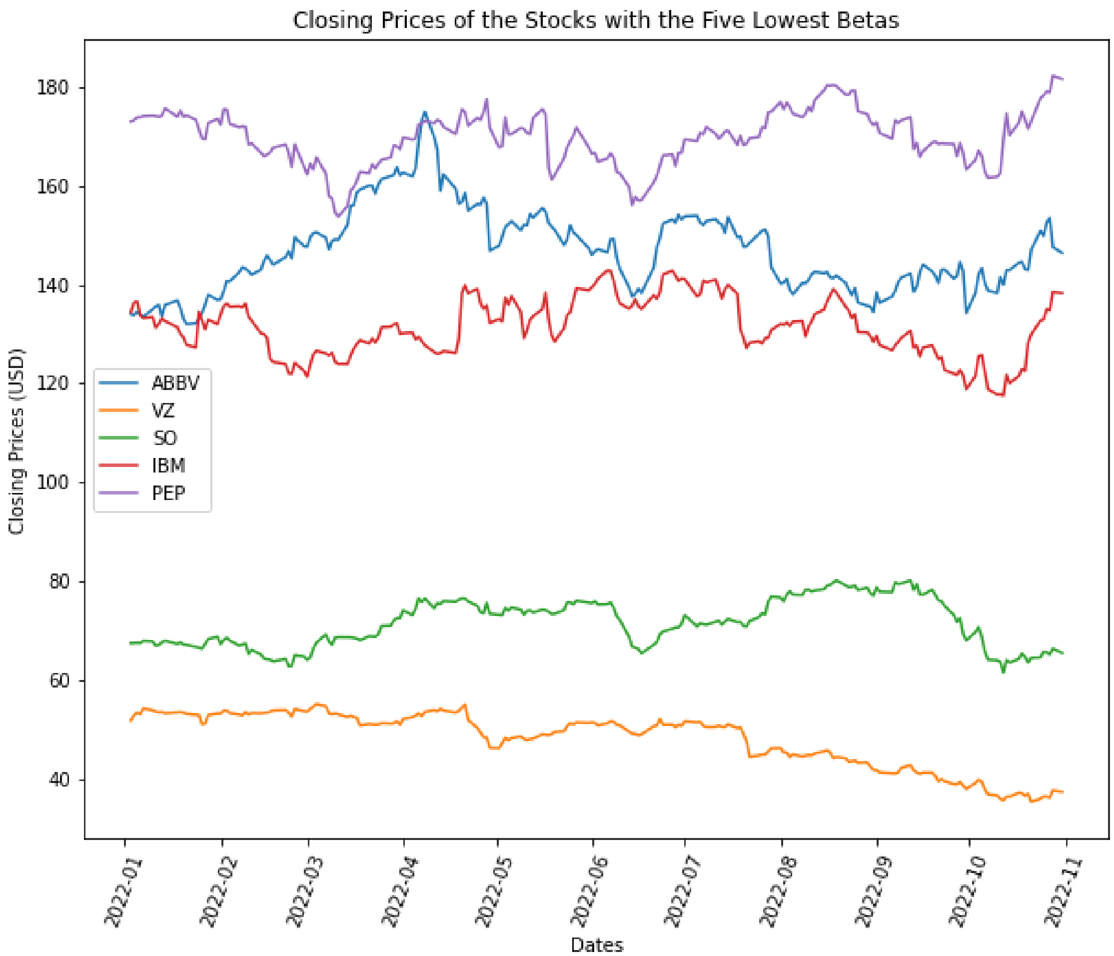
Here, we've calculated the correlation between the 2 stocks with the lowest beta values.

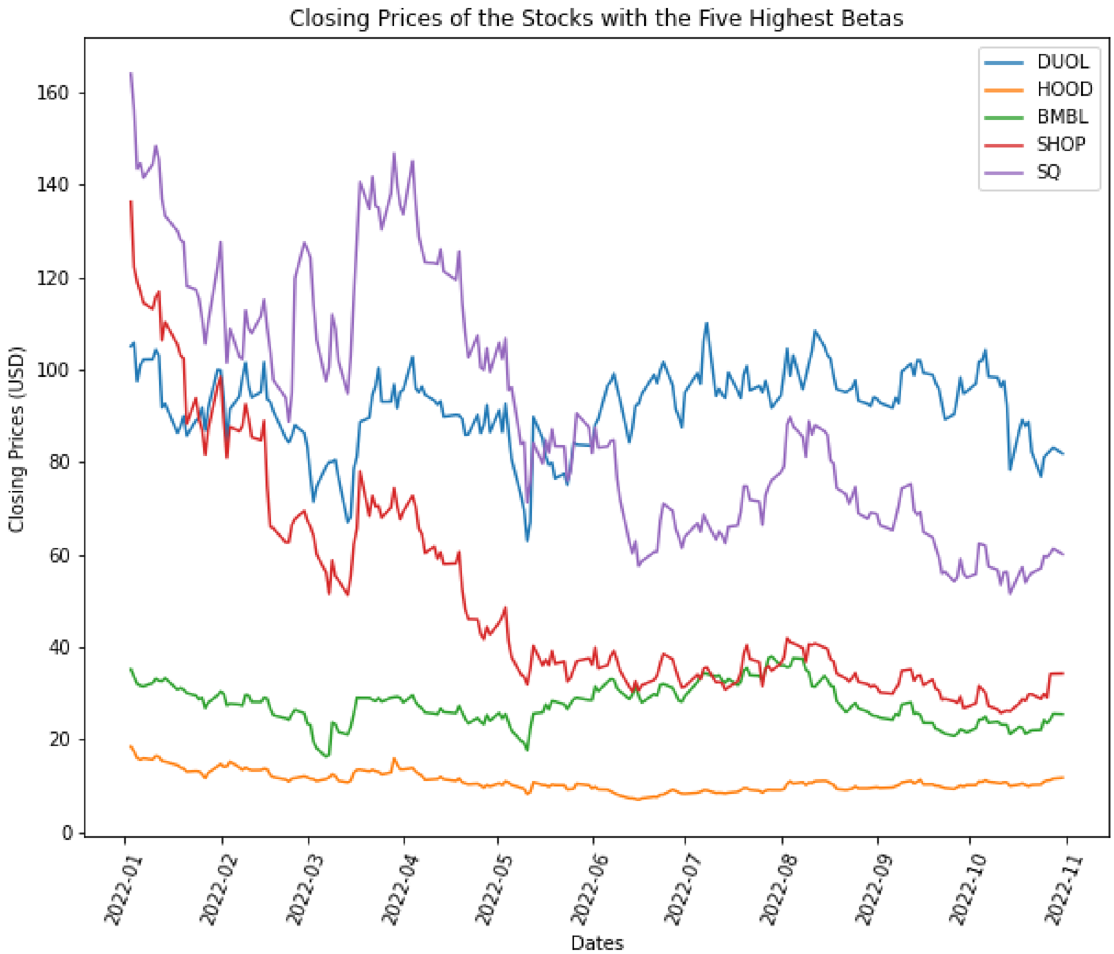
We can see from above that there is little correlation between the stocks. This means that as a result of having very little correlation with movements in the market, stocks with low beta will tend to have less correlation with each other as well.

[14]:

```
#A list of (Ticker, Closing Price) of the stocks with the 5 lowest betas.
lowest_beta_stock_prices = [(betas[:5][x][0], all_stocks[all_stocks.Names ==␣
↪betas[:5][x][0]].iloc[0].iloc[0].history(start=start, end=end)["Close"]) for␣
↪x in range(len(betas[:5]))]

#Graphing the closing prices for the stocks with the five lowest betas.
graph_data(lowest_beta_stock_prices)

plt.title("Closing Prices of the Stocks with the Five Lowest Betas")
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
#A list of (Ticker, Closing Price) of the stocks with the 5 highest betas.
highest_beta_stock_prices = [(betas[len(betas) - 5:][x][0],␣
↪all_stocks[all_stocks.Names == betas[len(betas) - 5:][x][0]].iloc[0].iloc[0].
↪history(start=start, end=end)["Close"]) for x in range(len(betas[(len(betas)␣
↪- 5):]))]

#Graphing the closing prices for the stocks with the five highest betas.
graph_data(highest_beta_stock_prices)
```

```python
plt.title("Closing Prices of the Stocks with the Five Highest Betas")
plt.xlabel("Dates")
plt.ylabel("Closing Prices (USD)")

plt.show()
```





Additionally, by comparing the above two graphs, we can see that stocks with lower betas tend to also experience less fluctuations. This is because a lower beta value indicates that the stock experiences less market risk. Consequently, stocks with lower betas will also be more stable and safe.

Due to these two key reasons, our program will prefer stocks with lower beta values compared to stocks with higher betas.

5 3. Scoring Each Stock

To put our portfolio together, we had to find a way to take into account each factor. However, certain factors were more important than others, which meant we also wanted to be able to control the weight of each factor. There was no existing function that could achieve our desired result, so we created our own function that assigned each stock a score: scoreNumeric. After playing around with different values and some discussion, we decided to weigh the different factors as follows:

Standard deviation: 90
Expected return: 100

Beta: 90

[15]:
```python
# Gives a score to each stock
def scoreNumeric(sorted_stocks, score_sorted=[], weight=100):
    # Sets a "standard" (the best score, so the rest of the stocks can compare)
    standard = sorted_stocks[0][1]
    # Sorts the list of stocks by name (so it can be matched with score_sorted)
    sorted_stocks.sort()
    if score_sorted != []:
        # Sort this one too so the indexes are the same (sorted by name)
        score_sorted.sort()

    for x in range(len(sorted_stocks)):
        # Finds the new score
        score = abs(weight * (standard / sorted_stocks[x][1]))
        name = sorted_stocks[x][0]
        stock = (name, score)
        if len(sorted_stocks) != len(score_sorted):
            score_sorted.append(stock)  # If the stock doesn't have a prev score
        else:
            # Add the scores together
            score_sorted[x] = (name, score + score_sorted[x][1])

    score_sorted.sort(key=lambda x:x[1], reverse=True)  # Return the list sorted

    return score_sorted
```

[16]:
```python
# Finds the scores of all eligible stocks based on these attributes
scores = scoreNumeric(all_std, [], 90)
scores = scoreNumeric(expected_returns, scores, 100)
scores = scoreNumeric(betas, scores, 90)
scores[0:5]
```

[16]:
```
[('SO', 182.88712997480107),
 ('AUST', 114.75908785800436),
 ('ABBV', 105.28801066109565),
 ('VZ', 97.72433017515633),
 ('IBM', 91.32554209614011)]
```

6 4. Diversification

Another component that we wanted our code to incorporate was diversification.

In essense, diversification aims to minimize risk by investing in different areas that should each react differently to changes in market conditions. Ideally, we would find companies that tend to move in opposite directions and have a negative correlation. To achieve this, we opted to "penalize" stocks if they were from the same sector or country as a stock we had already chosen to add to our portfolio. Simply put, after a stock was selected, the remaining stocks were "re-scored" based on the attributes (namely, sector and country) of the selected stock(s). The 'same sector penalty' is weighted at 10, whereas the 'same country penalty' is weighted at 2. These weightings are based on the assumption that we will be given a variety of stocks from different sectors, but most of these stocks will be American-based. We don't want diversification to override the other factors, so we adjusted the penalty weightings accordingly.

This strategy favoured inter-industry and international investments, and thereby promoted diversification in our portfolio, which simultaneously decreased risk and correlation between our stocks.

[17]:
```
# Gets a list of (category, number), where the number and category are based on
# the provided ev (list)
def inPortfolio(ev, category='sector'):
    sets = {}
    for stock in ev:
        try:
            # Add one to the proper category
            sets[all_stocks[all_stocks.Names == stock[0]].Info.
↪iloc[0][category]] += 1
        except KeyError:  # If it doesn't exist, it KeyErrors
            # Create the proper category
            sets[all_stocks[all_stocks.Names == stock[0]].Info.
↪iloc[0][category]] = 1

    # Creates the list
    set_list = [(stock, sets[stock]) for stock in sets]
    # Sorts in ascending order
    set_list.sort(key= lambda x:x[1])
    return set_list

# Creates the final portfolio by taking the scores
def createPortfolio(stocks_sorted, sec_weight=10, count_weight=2):
    # Represents the 25 stocks in the portfolio
    portfolio_list = []

    for x in range(25):
        # Add the highest rated stock into the portfolio
        portfolio_list.append(stocks_sorted[0])
        # Removes that stock from the list
        stocks_sorted.pop(0)

        # Find the list of industries and countries in the current portfolio
        industries_in_portfolio = inPortfolio(portfolio_list, 'sector')
        countries_in_portfolio = inPortfolio(portfolio_list, 'country')

        # Looking through the rest to adjust scores based on
        # diversification principles
        for x in range(len(stocks_sorted)):
            name = stocks_sorted[x][0]
```

```
            score = stocks_sorted[x][1]

            for pair in industries_in_portfolio:
                # if the current stocks sector is already in the portfolio
                if all_stocks[all_stocks.Names == name].Info.iloc[0]['sector']␣
 ↪== pair[0]:
                    # Apply a score penalty based on how many
                    # stocks of that sector are already in the portfolio
                    stocks_sorted[x] = (name, score - (sec_weight * pair[1]))

            for pair in countries_in_portfolio:
                # if the current stocks country is already in the portfolio
                if all_stocks[all_stocks.Names == name].Info.iloc[0]['country']␣
 ↪== pair[0]:
                    # Apply a score penalty based on how many
                    # stocks of that country are already in the portfolio
                    stocks_sorted[x] = (name, score - (count_weight * pair[1]))

        # Sort the list each time to bring the best stock to the top
        stocks_sorted.sort(key=lambda x:x[1], reverse=True)

    # Return a list of the best 25 tickers (names)
    portfolio_list = [name[0] for name in portfolio_list]
    return portfolio_list

# list of the best tickers
tickers = createPortfolio(scores.copy())
```

7 5. Creating the Portfolio

In this last chunk of code, we are putting together the portfolio in a dataframe with the appropriate columns, as well as outputting the dataframe to a CSV file, as required by the specifications of the assignment.

[18]:
```
# Date for the price is November 25th 2022
date = '2022-11-25'  # '2022-01-01'
date_1 = '2022-11-26'  # '2022-11-01'

# Weights for each stock is 4%
weights_for_all = 0.04
price = 500000

# Creates the final portfolio with the requested columns
Portfolio_Final = pd.DataFrame(columns=['Ticker', 'Price', 'Shares', 'Value',␣
 ↪'Weight', 'Index'])
# Tickers
```

```
Portfolio_Final['Ticker'] = tickers
# Prices based on the close price of Date (November 25th 2022)
Portfolio_Final['Price'] = [all_stocks[all_stocks.Names == tick].iloc[0].
 ↪iloc[0].history(start=date, end=date_1)["Close"][0] for tick in tickers]
# Shares is the total budget (500000 * weight) divided by the price
Portfolio_Final['Shares'] = price * weights_for_all / Portfolio_Final['Price']
# Value is the price pre share times the number of shares
Portfolio_Final['Value'] = Portfolio_Final['Shares'] * Portfolio_Final['Price']
# All weights are 4%, so create a list of 4s
Portfolio_Final['Weight'] = [weights_for_all * 100 for x in range(25)]
# Create the new index (1, 25)
Portfolio_Final['Index'] = list(range(1,26))
Portfolio_Final.set_index('Index', inplace=True)

Portfolio_Final.head()
```

[18]:

Index	Ticker	Price	Shares	Value	Weight
1	SO	66.910004	298.908966	20000.0	4.0
2	AUST	1.040000	19230.769936	20000.0	4.0
3	ABBV	159.619995	125.297586	20000.0	4.0
4	VZ	39.020000	512.557657	20000.0	4.0
5	IBM	148.369995	134.798144	20000.0	4.0

[19]:
```
# Stocks_Final is Portfolio_Final but with less columns
Stocks_Final = Portfolio_Final.drop(['Price', 'Value', 'Weight'], axis=1)
# Send the dataframe to a csv file (without index)
Stocks_Final.to_csv('Stocks_Group_10.csv', index=True)
Stocks_Final
```

[19]:

Index	Ticker	Shares
1	SO	298.908966
2	AUST	19230.769936
3	ABBV	125.297586
4	VZ	512.557657
5	IBM	134.798144
6	PEP	108.630710
7	CVS	197.511353
8	SLB	393.468410
9	SHOP	543.625972
10	CMCSA	561.009794
11	ORCL	241.779494
12	OXY	284.575987
13	CSCO	413.223127
14	BAC	530.503968
15	COST	37.477047

```
16        BK    437.924257
17       JPM    146.262975
18       LOW     94.800208
19       AXP    129.743761
20      HOOD   2129.925375
21       SPG    165.700087
22      AAPL    135.034771
23        GM    494.315384
24      GOOG    204.918036
25      DUOL    286.985210
```

[20]:

```python
# Print out the requested information
print("The total weight of the portfolio is: %.2f" % Portfolio_Final.Weight.
 ↪sum())
print("The total price of the portfolio at the start date is: $%.2f" %␣
 ↪(Portfolio_Final.Price * Portfolio_Final.Shares).sum())
Portfolio_Final
```

```
The total weight of the portfolio is: 100.00
The total price of the portfolio at the start date is: $500000.00
```

[20]:

Index	Ticker	Price	Shares	Value	Weight
1	SO	66.910004	298.908966	20000.0	4.0
2	AUST	1.040000	19230.769936	20000.0	4.0
3	ABBV	159.619995	125.297586	20000.0	4.0
4	VZ	39.020000	512.557657	20000.0	4.0
5	IBM	148.369995	134.798144	20000.0	4.0
6	PEP	184.110001	108.630710	20000.0	4.0
7	CVS	101.260002	197.511353	20000.0	4.0
8	SLB	50.830002	393.468410	20000.0	4.0
9	SHOP	36.790001	543.625972	20000.0	4.0
10	CMCSA	35.650002	561.009794	20000.0	4.0
11	ORCL	82.720001	241.779494	20000.0	4.0
12	OXY	70.279999	284.575987	20000.0	4.0
13	CSCO	48.400002	413.223127	20000.0	4.0
14	BAC	37.700001	530.503968	20000.0	4.0
15	COST	533.659973	37.477047	20000.0	4.0
16	BK	45.669998	437.924257	20000.0	4.0
17	JPM	136.740005	146.262975	20000.0	4.0
18	LOW	210.970001	94.800208	20000.0	4.0
19	AXP	154.149994	129.743761	20000.0	4.0
20	HOOD	9.390000	2129.925375	20000.0	4.0
21	SPG	120.699997	165.700087	20000.0	4.0
22	AAPL	148.110001	135.034771	20000.0	4.0
23	GM	40.459999	494.315384	20000.0	4.0
24	GOOG	97.599998	204.918036	20000.0	4.0

```
25       DUOL    69.690002     286.985210  20000.0      4.0
```

7.1 Contribution Declaration

The following team members made a meaningful contribution to this assignment:

Arteen Mirzaei

Momina Butt

Avi Dave

Code Corrections (Second Submission): In total, there were two errors in the code, one that crashed the program, and one that resulted in an unexpected output. The first error was not removing the index QQQ, which caused a KeyError when accessing information. The code was update to remove non-equity tickers, which would remove the index(es). The second error was not removing the duplicate "SHOP" tickers. Though the code doesn't crash, it does ends up putting the same stock in the portfolio 3 times. This is unintended. The code was updated to remove duplicate tickers when reading the csv file.