1- Data Prep & EDA: S&P 500 Company Stocks in Consumer Staples, Energy & Financial Sectors

OPIM 5641: Business Decision Modeling - University of Connecticut - GROUP-4

Raw data download and description: Yahoo Finance

Intro: In the world of investing, selecting the right stocks is like assembling a winning team. Our goal is to create a smart and reliable portfolio by carefully picking 30 stocks from the S&P 500 companies. We're focusing on companies showing positive trends and less volatility, aiming for a stable and promising investment journey. This strategic approach ensures that our portfolio is well-positioned for success, offering growth potential while minimizing risks. Let's dive into the world of these carefully chosen stocks, shaping a portfolio that aligns with our vision for financial success.

```
# This code chunk mounts your Google Drive in Colab thereby connecting your Colab environme
# so that you can access files and data stored in your Drive.
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Import Necessary Modules

[ ] ↳ *3 cells hidden*

1.1 - Stock Selection and Data extraction

In this piece of code, we're scraping historical stock prices from a selection of 30 stocks, with 10 stocks from each of three sectors: Consumer Staples, Energy, and Financials. The time range for this data spans from January 1, 2017, to December 31, 2021. The outcome is a data frame that sets the stage for our upcoming analysis.

```
# Defining lists of ticker symbols for 10 companies each that we chose for different sector
# 'con_tickers' for Consumer Staples, 'energy_tickers' for Energy, and 'fin_tickers' for Fi
con_tickers = ['COST','DLTR','PEP','PG','WMT','EL','CL','MO','CLX','SYY']
energy_tickers = ['HES','PSX','DVN','CTRA','WMB','FANG','APA','XOM','OKE','VLO']
fin_tickers = ['JPM','IVZ','GS','DFS','KEY','MA','PRU','SPGI','WFC','V']
# Fetching historical price data for each stock from date range 01/01/2017 to 12/31/2021
con_dod_prices = {ticker : si.get_data(ticker,start_date = '01/01/2017',end_date='12/31/202
energy_dod_prices = {ticker : si.get_data(ticker,start_date = '01/01/2017',end_date='12/31/
fin_dod_prices = {ticker : si.get_data(ticker,start_date = '01/01/2017',end_date='12/31/202
```

```
# Commenting this block since output is as expected for the next steps
# Uncomment the next line to print Consumer Staples Sector prices
# con_dod_prices
# Uncomment the next line to print Energy Sector prices
# energy_dod_prices
# Uncomment the next line to print Financials Sector prices
# fin_dod_prices
```

So, when you run the lines above ex: con_dod_prices , you create con_dod_prices, a dictionary. Each company in Consumer Staples, like Costco ('COST') or Pepsi ('PEP'), gets a detailed stock report. The data covers opening, high, low, and closing prices, trading volume, and dividends from January 1, 2017, to December 31, 2021. It's like a quick way to see how each company's stock did over those years. Just use the ticker symbol to check their specific data.

During the data cleaning phase, we focus on extracting the 'adjclose' prices, as they hold significant importance for our subsequent financial analysis. These adjusted closing prices serve as key indicators for our further steps in the analysis, providing a refined dataset for more accurate insights.

```
# Initializing 'prepdata' with sample stock data to avoid potential errors.
# Creating DataFrames for a sample stock in each sector:
# 'COST' for Consumer Staples, 'HES' for Energy, and 'JPM' for Finance.

con_data = pd.DataFrame(con_dod_prices['COST']['adjclose']).rename(columns = {"adjclose":"C
energy_data = pd.DataFrame(energy_dod_prices['HES']['adjclose']).rename(columns = {"adjclos
fin_data = pd.DataFrame(fin_dod_prices['JPM']['adjclose']).rename(columns = {"adjclose":"JP

# Extracting the 'adjclose' data for all tickers in each sector and adding it to the respec
# Looping through Consumer Staples tickers.
for i in con_tickers[1:]:
    con_data[i] = pd.DataFrame(con_dod_prices[i]['adjclose'])

# Looping through Energy tickers.
for i in energy_tickers[1:]:
    energy_data[i] = pd.DataFrame(energy_dod_prices[i]['adjclose'])

# Looping through Finance tickers.
for i in fin_tickers[1:]:
    fin_data[i] = pd.DataFrame(fin_dod_prices[i]['adjclose'])



# When uncommented, the lines below will display the DataFrame containing the adjusted clos
# con_data
# energy_data
# fin_data


# Checking for null values
for key, value in con_data.items():
    if value is None:
        print(key, 'has a null value')

    else:
        print(key, 'has no null values')
```

```
COST has no null values
DLTR has no null values
PEP has no null values
PG has no null values
WMT has no null values
EL has no null values
CL has no null values
MO has no null values
CLX has no null values
SYY has no null values
```

```
# Checking for null values
for key, value in energy_data.items():
    if value is None:
        print(key, 'has a null value')

    else:
        print(key, 'has no null values')
```

```
HES has no null values
PSX has no null values
DVN has no null values
CTRA has no null values
WMB has no null values
FANG has no null values
APA has no null values
XOM has no null values
OKE has no null values
VLO has no null values
```

```
# Checking for null values
for key, value in fin_data.items():
    if value is None:
        print(key, 'has a null value')

    else:
        print(key, 'has no null values')
```

```
JPM has no null values
IVZ has no null values
GS has no null values
DFS has no null values
KEY has no null values
MA has no null values
PRU has no null values
SPGI has no null values
WFC has no null values
V has no null values
```

Since there are no null values we are not dropping anything.

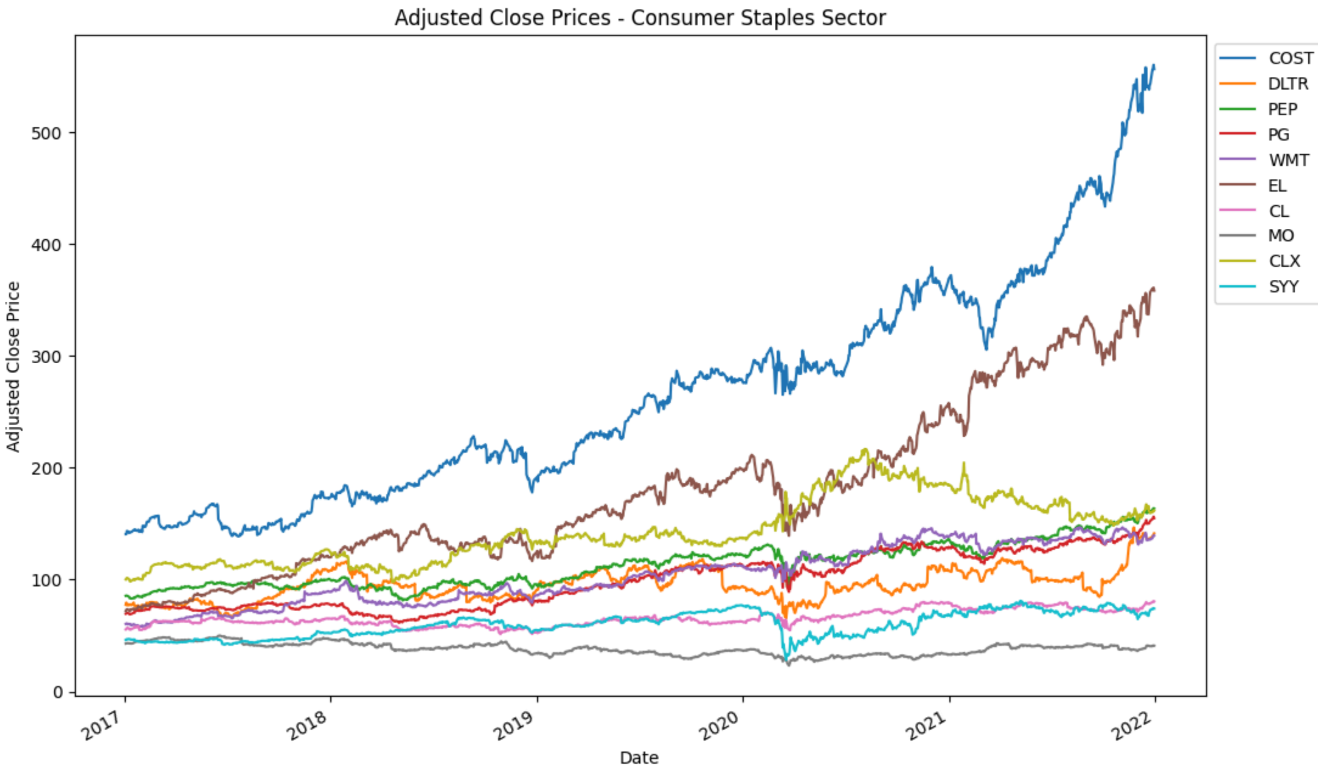
```
# data shape
print(con_data.shape, energy_data.shape, fin_data.shape)
```

```
(1258, 10) (1258, 10) (1258, 10)
```

1.2 - Visualizations

```
# Importing necessary libraries for plotting
import matplotlib.pyplot as plt

# Plotting a line graph for each ticker in 'con_data'
con_data.plot(figsize=(12, 8), title='Adjusted Close Prices - Consumer Staples Sector')
plt.xlabel('Date')
plt.ylabel('Adjusted Close Price')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
```

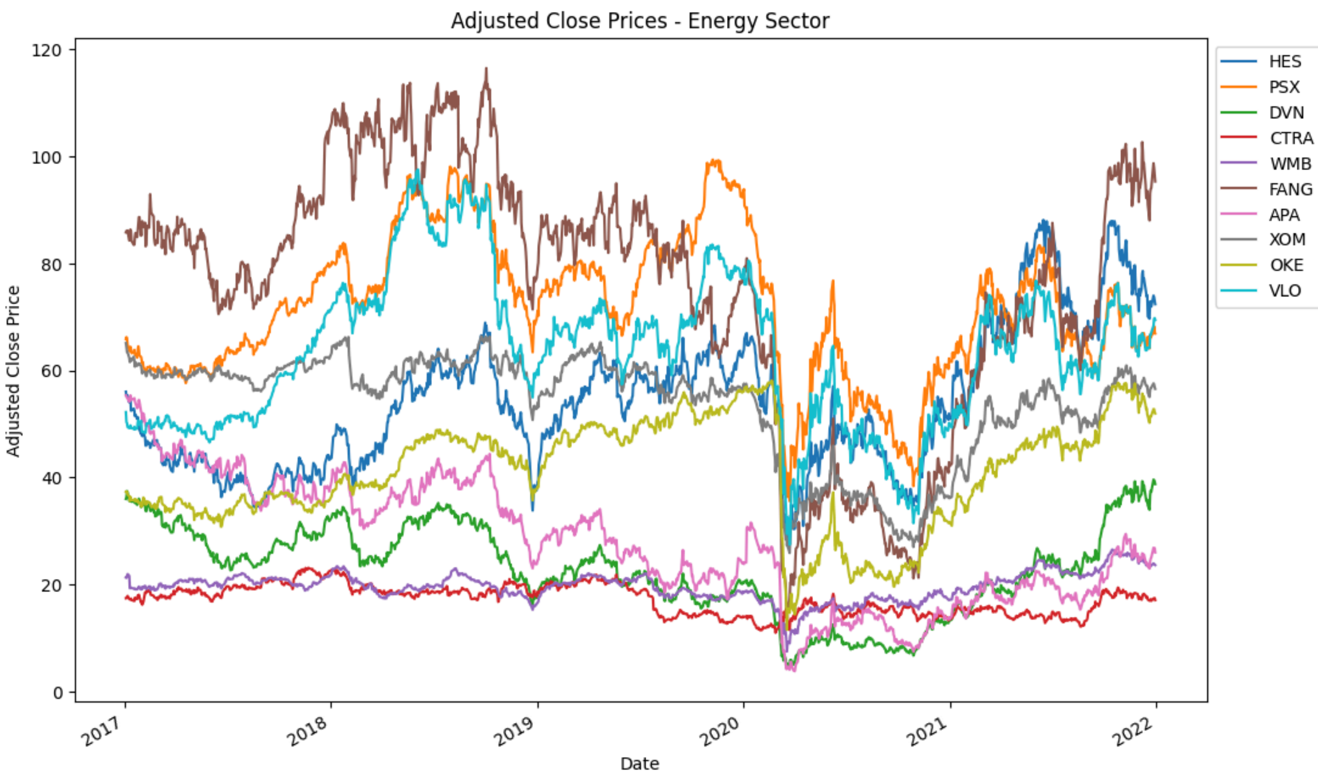


1.3.1 - What I see in visualization plot for Consumer staples sector

Looking at the time-series graph for the Consumer Staples sector, PEP (PepsiCo) emerges as a compelling choice among other stocks ('COST', 'DLTR', 'PG', 'WMT', 'EL', 'CL', 'MO', 'CLX', 'SYY'). PEP exhibits a steady and consistently positive trend throughout the 2017 to 2022 period. This stable performance suggests resilience and reliability, making PEP an attractive option for investors seeking a less volatile and more predictable investment in the Consumer Staples sector.

```
# Importing necessary libraries for plotting
import matplotlib.pyplot as plt

# Plotting a line graph for each ticker in 'con_data'
energy_data.plot(figsize=(12, 8), title='Adjusted Close Prices - Energy Sector')
plt.xlabel('Date')
plt.ylabel('Adjusted Close Price')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
```

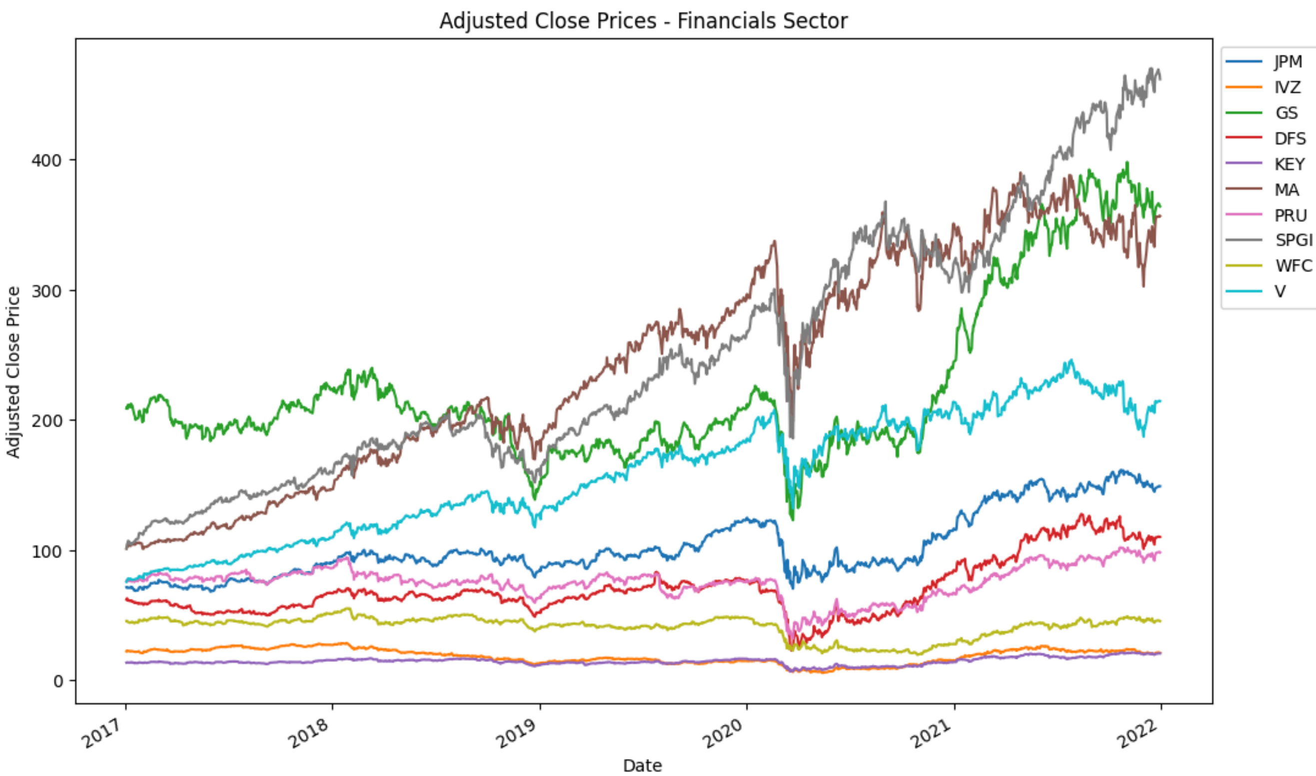


1.3.2 - What I see in visualization plot for Energy sector

Amongst the stocks in the Energy sector from 2017 to 2022, 'XOM' stands out as a compelling choice. ExxonMobil ('XOM') exhibits a steadiness reminiscent of 'WMB', displaying consistent returns with relatively lower volatility. This stability, coupled with a resilient performance even during market downturns, positions 'XOM' as an ideal choice for investors seeking a balanced and reliable investment in the energy market. Its ability to weather uncertainties sets it apart from the more volatile options, making 'XOM' a prudent selection for a resilient investment strategy.

```
# Importing necessary libraries for plotting
import matplotlib.pyplot as plt

# Plotting a line graph for each ticker in 'con_data'
fin_data.plot(figsize=(12, 8), title='Adjusted Close Prices - Financials Sector')
plt.xlabel('Date')
plt.ylabel('Adjusted Close Price')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
```



1.3.3 - What I see in visualization plot for Financials sector

JPMorgan Chase & Co. (JPM) emerges as a compelling choice within the financials sector, showcasing intriguing volatility dynamics from 2017 to 2021. The stock experiences relatively low volatility in the initial years, with a notable spike during specific periods, providing a nuanced view of its market behavior. JPM's overall trend and volatility patterns contribute to its significance in the financial sector, offering us valuable information for strategic decision-making.

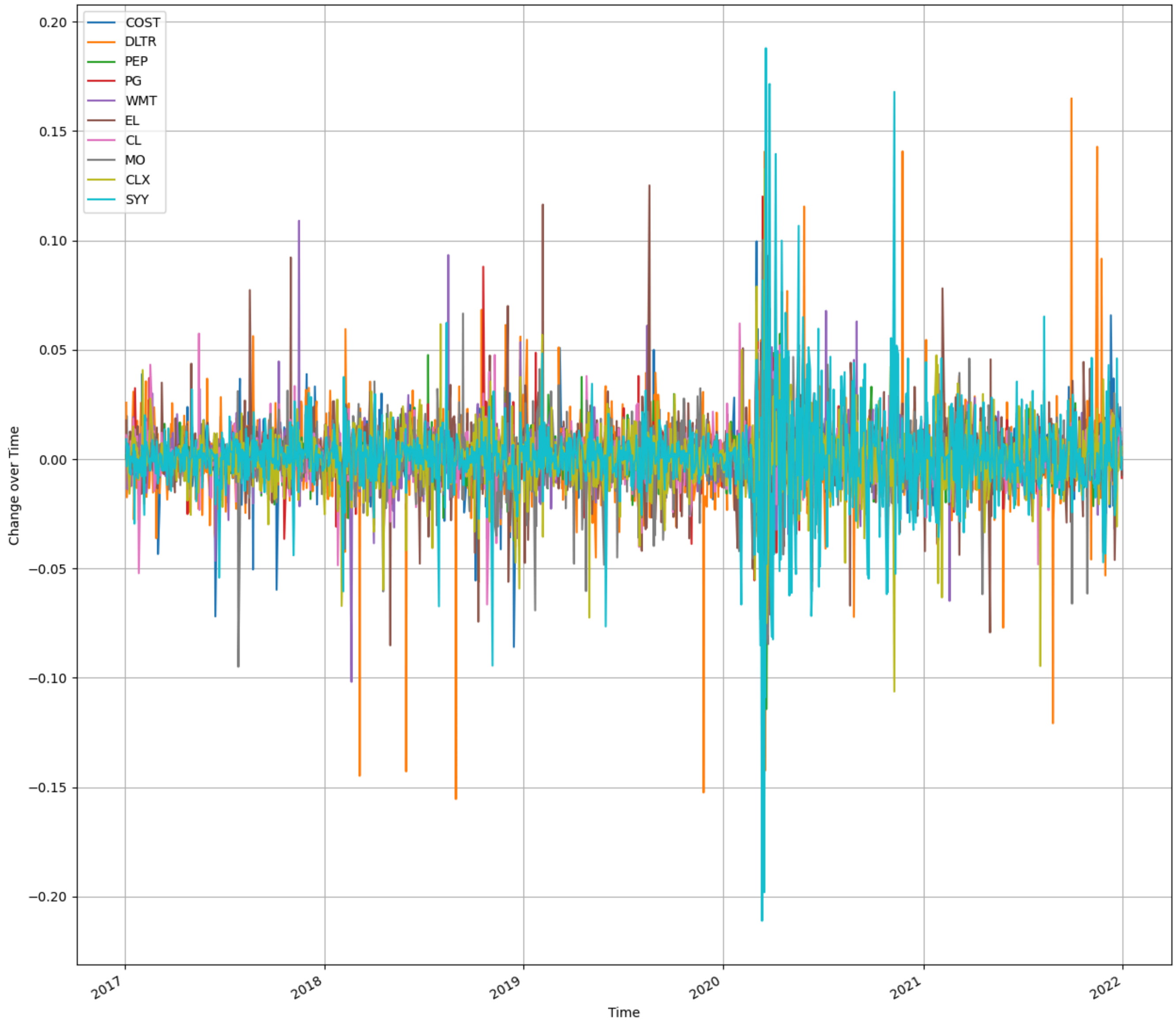
1.4 - Calculation of differences from previous days

```
# creating return features for each ticker in Consumer Staples Sector
# we will use a pct_change - shows the fractional change in values over a series of time. U
return_con_data = pd.DataFrame()
for i in con_tickers:
  return_con_data[i] = con_data[i].pct_change()
# drop the na records
return_con_data.dropna(inplace=True)
return_con_data
```

	COST	DLTR	PEP	PG	WMT	EL	CL	MO
2017-01-04	0.000188	0.025823	0.001911	0.003564	0.005826	0.017716	0.010986	0.003253
2017-01-05	0.019717	-0.017495	-0.001335	0.006627	0.002172	-0.001271	0.008904	0.001179
2017-01-06	-0.000491	-0.012426	-0.001433	-0.000352	-0.013726	0.007125	0.007629	0.004416
2017-01-09	-0.011423	0.000649	-0.010520	-0.007409	0.006593	-0.011622	-0.013955	-0.004104
2017-01-10	0.004287	0.010630	-0.014402	-0.010782	-0.006986	-0.011375	-0.015507	-0.003385
...	...	...	...	...	...	...	...	...
2021-12-23	0.001274	0.003516	-0.001118	0.004896	-0.002217	0.011861	0.004002	-0.003840
2021-12-27	0.023802	0.010730	0.009954	0.011680	0.009104	0.008962	0.013528	0.001927
2021-12-28	0.002076	0.005922	0.005190	0.005371	0.014351	-0.003981	0.006554	0.012610
2021-12-29	0.005543	0.007251	0.003539	0.008290	-0.000490	0.006199	0.005328	0.000422
2021-12-30	-0.006798	0.006914	-0.001734	-0.008648	0.003223	-0.007404	-0.003769	-0.003165

1257 rows × 10 columns

```
return_con_data.plot(
        grid=True,
        layout=(3,3),
         figsize=(15,15),xlabel='Time',ylabel='Change over Time')
plt.show()
```

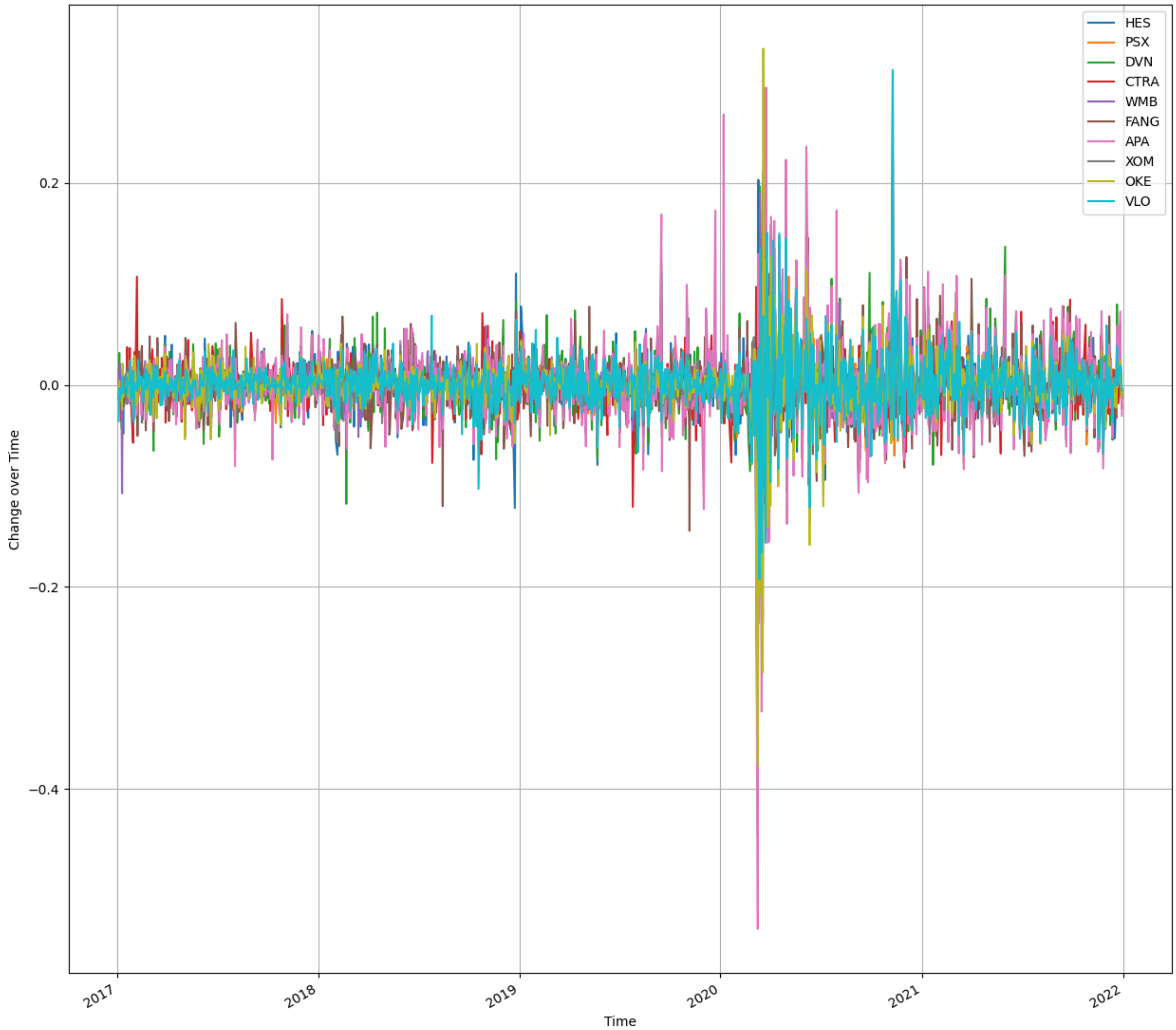



```
# creating return features for each ticker in Energy Sector
return_energy_data = pd.DataFrame()
for i in energy_tickers:
  return_energy_data[i] = energy_data[i].pct_change()
# drop the na records
return_energy_data.dropna(inplace=True)
return_energy_data
```

	HES	PSX	DVN	CTRA	WMB	FANG	APA	XOM
2017-01-04	-0.014168	0.005415	0.008921	0.001343	-0.003179	0.003099	-0.002979	-0.011002
2017-01-05	0.002745	-0.005959	0.031789	0.012070	0.012118	0.000965	-0.005346	-0.014907
2017-01-06	-0.003221	-0.015448	-0.006937	0.011042	0.021424	-0.000096	-0.002055	-0.000564
2017-01-09	-0.020840	-0.016159	-0.042942	-0.034949	-0.015114	-0.021513	-0.012041	-0.016497
2017-01-10	0.013859	-0.003094	0.002576	0.003621	-0.107422	0.012620	0.008178	-0.012753
...	...	...	...	...	...	...	...	...
2021-12-23	-0.008366	0.003910	-0.005675	-0.018228	0.006620	0.002365	0.009291	0.000492
2021-12-27	0.028848	0.012378	0.060880	0.026818	0.015861	0.049084	0.072881	0.014258
2021-12-28	-0.004365	0.015661	-0.002466	0.002511	-0.003808	-0.008818	-0.001430	-0.003232
2021-12-29	-0.008103	-0.014608	-0.006742	0.002505	-0.004587	-0.013163	-0.000716	-0.008753
2021-12-30	-0.009508	-0.005491	-0.011991	-0.022989	-0.004608	-0.012878	-0.030455	-0.005887

1257 rows × 10 columns

```
return_energy_data.plot(
        grid=True,
        layout=(3,3),
         figsize=(15,15),xlabel='Time',ylabel='Change over Time')
plt.show()
```

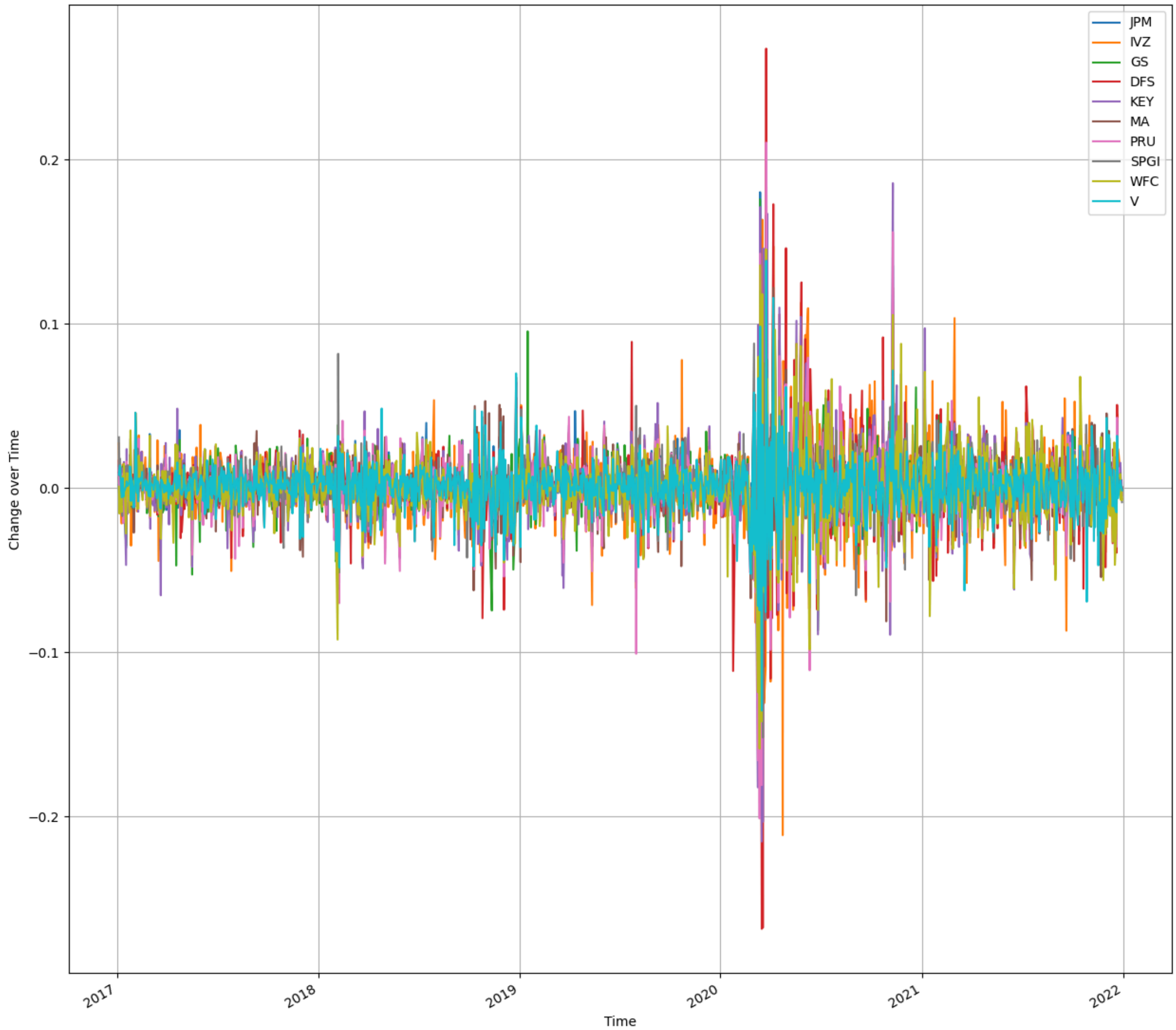



```
# creating return features for each ticker in Financials Sector
return_fin_data = pd.DataFrame()
for i in fin_tickers:
  return_fin_data[i] = fin_data[i].pct_change()
# drop the na records
return_fin_data.dropna(inplace=True)
return_fin_data
```

	JPM	IVZ	GS	DFS	KEY	MA	PRU	SPGI
2017-01-04	0.001844	0.027158	0.006458	0.016637	0.013691	0.009489	0.012207	0.030907
2017-01-05	-0.009205	-0.007869	-0.007445	-0.014066	-0.012425	0.007723	-0.014980	0.007607
2017-01-06	0.000116	0.000317	0.014835	-0.011523	0.002188	0.007197	0.005739	0.017852
2017-01-09	0.000697	-0.021567	-0.008207	-0.006106	-0.003275	-0.001949	-0.003899	-0.011518
2017-01-10	0.002901	-0.005835	-0.001317	0.006842	0.012048	-0.002138	0.007924	-0.017038
...	...	...	...	...	...	...	...	...
2021-12-23	0.003574	0.023684	0.007088	0.004179	0.003530	0.008672	0.012534	0.001014
2021-12-27	0.005723	0.008997	0.007791	0.006763	0.015391	-0.000749	0.005358	0.009203
2021-12-28	0.003035	-0.000849	-0.001108	-0.000431	0.004331	0.001304	0.002114	-0.006275
2021-12-29	-0.000504	-0.007225	-0.003638	-0.002585	0.004743	0.001414	0.000183	-0.001158
2021-12-30	-0.000505	-0.006421	-0.001761	0.000518	-0.004721	-0.000830	-0.004125	-0.008576

1257 rows × 10 columns

```
return_fin_data.plot(
        grid=True,
        layout=(3,3),
         figsize=(15,15),xlabel='Time',ylabel='Change over Time')
plt.show()
```




```
# data check
print(return_con_data.shape, return_energy_data.shape, return_fin_data.shape)
```

```
(1257, 10) (1257, 10) (1257, 10)
```

2 - Momentum Trading for Stock Selection: S&P 500 Company Stocks in Consumer Staples, Energy & Financial Sectors

In this section, our goal is to calculate returns based on buy and sell conditions related to moving averages.

2.1 - Data Prep to Prepare for Momentum Trading

In this section we are preping as well as adding columns to support Momemtum Trading. A key part of the momentum trading strategy relies on the 8 and 21 day moving averages. If we were to take the data starting at the first of the year, our moving averages wouldnt be true 8 and 21 day moving averages. To adjust for this, we are taking data all the way back from December of 2020 to ensure we have 8 and 21 day moving averages come the first of the year.

```
# Convert the index to datetime format
con_data.index = pd.to_datetime(con_data.index)
energy_data.index = pd.to_datetime(energy_data.index)
fin_data.index = pd.to_datetime(fin_data.index)

# Extract data for the year 2021 (starting in late 2020 for reasons listed above)
con_data_2021 = con_data.loc['2020-12-02':'2021-12-31']
energy_data_2021 = energy_data.loc['2020-12-02':'2021-12-31']
fin_data_2021 = fin_data.loc['2020-12-02':'2021-12-31']

# Display the DataFrame for the year 2021
#print(con_data_2021)

#for visualization and confirmation
# con_data_2021.head(10)
# energy_data_2021.head(10)
fin_data_2021.head(10)
```

	JPM	IVZ	GS	DFS	KEY	MA	PRU	
2020-12-02	112.067200	14.941596	220.556427	76.476952	13.843637	334.546021	67.960793	324.
2020-12-03	111.332573	15.868760	218.533264	75.681175	13.852316	329.550659	68.124916	318.
2020-12-04	112.342682	15.859846	222.347610	77.422501	13.991185	338.607086	70.215225	330.
2020-12-07	111.920280	16.064894	221.298920	77.188461	13.774201	335.273621	69.083687	327.
2020-12-08	112.030464	16.109468	221.660858	76.720360	13.852316	335.106506	69.316910	324.
2020-12-09	111.158112	15.779611	225.354568	77.881226	13.930429	331.232178	69.299629	318.
2020-12-10	110.441841	15.610226	226.820908	78.789322	13.956470	325.991089	69.066422	317.
2020-12-11	109.789879	15.922251	222.728134	78.133995	13.748164	321.959442	67.874413	316.
2020-12-14	108.632835	15.244708	220.686386	77.356956	13.392308	325.627228	66.172798	315.
2020-12-15	110.487762	15.681547	224.992615	79.912750	13.617972	328.085541	67.209335	315.

```
Day_con = np.arange(1, len(con_data_2021) + 1) #generate list of trading days for consumer
Day_energy = np.arange(1, len(energy_data_2021) + 1) #generate list of trading days for ene
Day_fin = np.arange(1, len(con_data_2021) + 1) #generate list of trading days for fin

#here we are adding a Day Column that will be helpful in determine moving averages
con_data_2021.insert(0, 'Day', Day_con)
energy_data_2021.insert(0, 'Day', Day_energy)
fin_data_2021.insert(0, 'Day', Day_fin)
#displaying just consumer staple to ensure accuracy
con_data_2021.head()
```

	Day	COST	DLTR	PEP	PG	WMT	EL
2020-12-02	1	375.224915	111.629997	132.093033	128.435425	143.687714	237.518768	79.7814
2020-12-03	2	365.978790	112.120003	132.877701	127.488579	142.523102	237.654297	79.2697
2020-12-04	3	365.372192	112.510002	134.165543	127.609268	142.150818	236.356918	79.1208
2020-12-07	4	365.274323	111.949997	133.724030	127.804214	141.387115	237.944778	79.4558
2020-12-08	5	369.452209	109.459999	133.861984	128.147644	142.666275	240.578278	79.2510

Here we are checking for any null values that could cause issues when calculating averages.

```
con_data_2021.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 272 entries, 2020-12-02 to 2021-12-30
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Day     272 non-null    int64
 1   COST    272 non-null    float64
 2   DLTR    272 non-null    float64
 3   PEP     272 non-null    float64
 4   PG      272 non-null    float64
 5   WMT     272 non-null    float64
 6   EL      272 non-null    float64
 7   CL      272 non-null    float64
 8   MO      272 non-null    float64
 9   CLX     272 non-null    float64
 10  SYY     272 non-null    float64
dtypes: float64(10), int64(1)
memory usage: 25.5 KB
```

2.2 - Moving Averages

Here we are calculating the moving averages for each stock in each sector, a key piece in Momentum Trading. For this, we will consider 8 and 21 day moving averages.

```
columns_to_process_con = con_data_2021.columns[1:]  # Exclude the 'Day' and index columns
columns_to_process_energy = energy_data_2021.columns[1:]  # Exclude the 'Day' and index col
columns_to_process_fin = fin_data_2021.columns[1:]  # Exclude the 'Day' and index columns

# Creating a new DataFrame to store moving averages
moving_averages_con = pd.DataFrame()
moving_averages_energy = pd.DataFrame()
moving_averages_fin = pd.DataFrame()

# Loop through each column (excluding the first two columns) and calculate moving averages
for column in columns_to_process_con:
    # Calculate 8-day and 21-day moving averages
    moving_averages_con.loc[:, '{}-day-8'.format(column)] = con_data_2021[column].rolling(8
    moving_averages_con.loc[:, '{}-day-21'.format(column)] = con_data_2021[column].rolling(

for column in columns_to_process_energy:
    # Calculate 8-day and 21-day moving averages
    moving_averages_energy.loc[:, '{}-day-8'.format(column)] = energy_data_2021[column].rol
    moving_averages_energy.loc[:, '{}-day-21'.format(column)] = energy_data_2021[column].ro

for column in columns_to_process_fin:
    # Calculate 8-day and 21-day moving averages
    moving_averages_fin.loc[:, '{}-day-8'.format(column)] = fin_data_2021[column].rolling(8
    moving_averages_fin.loc[:, '{}-day-21'.format(column)] = fin_data_2021[column].rolling(

# Drop rows with NaN values
moving_averages_con.dropna(inplace=True)
moving_averages_energy.dropna(inplace=True)
moving_averages_fin.dropna(inplace=True)

#Displaying for validation
moving_averages_con.head()
```

	COST-day-8	COST-day-21	DLTR-day-8	DLTR-day-21	PEP-day-8	PEP-day-21	PG-day-8
2021-01-04	360.607269	363.673001	108.752501	109.947143	134.398987	133.842590	127.885427
2021-01-05	362.463825	363.516918	108.180001	109.723810	134.269056	133.872071	127.920237
2021-01-06	364.140594	363.595657	107.948750	109.486191	134.347244	133.883022	128.169713
2021-01-07	365.134911	363.436779	108.617500	109.508096	134.177061	133.755115	128.612960
2021-01-08	365.543407	363.184723	109.332500	109.641429	133.879246	133.628082	128.744076

Notice here the first day of the 8 and 21 day moving averages is January 4th. This is the first trading day of 2021 so this is as expected. If we did not start in December of 2020, our 8 and 21 day averages values would have started in the first week of Janaury.

2.3 - Returns

Here we are calculating returns for each stock in each sector which with we will eventually have to manipulate to calculate the system return which will show us the top performing stocks in each sector.

```
# Iterate over each stock and calculate the corresponding 'returns' column
stock_names_con = con_data_2021.columns[1:]  # Exclude the 'Day' column
stock_names_energy = energy_data_2021.columns[1:]
stock_names_fin = fin_data_2021.columns[1:]

for stock_name in stock_names_con:
  returns_col_con = f"{stock_name}-return"
  # Calculate log returns
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
  # Store the returns column in moving_averages_df
  moving_averages_con[returns_col_con] = con_data_2021[returns_col_con]
for stock_name in stock_names_energy:
  returns_col_energy = f"{stock_name}-return"
  # Calculate log returns
  energy_data_2021[returns_col_energy] = np.log(energy_data_2021[stock_name]).diff()
  # Store the returns column in moving_averages_df
  moving_averages_energy[returns_col_energy] = energy_data_2021[returns_col_energy]
for stock_name in stock_names_fin:
  returns_col_fin = f"{stock_name}-return"
  # Calculate log returns
  fin_data_2021[returns_col_fin] = np.log(fin_data_2021[stock_name]).diff()
  # Store the returns column in moving_averages_df
  moving_averages_fin[returns_col_fin] = fin_data_2021[returns_col_fin]
```

```
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
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<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
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<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

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<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  con_data_2021[returns_col_con] = np.log(con_data_2021[stock_name]).diff()
<ipython-input-27-f656fb5bef33>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

2.4 - Invested Column

Here we are adding an invested column to show whether we are currently in the market with that particular stock or if we are out of the market. A value of 1 denoties that the 8- day average is greater than the 21 day moving average and we are therefore invested. 0 means we are not currently invested.

```
#List of stock names by extracting the prefix before '-day-'
stock_names_con = set(col.split('-')[0] for col in moving_averages_con.columns)
stock_names_energy = set(col.split('-')[0] for col in moving_averages_energy.columns)
stock_names_fin = set(col.split('-')[0] for col in moving_averages_fin.columns)

# Iterate over each stock and create the corresponding 'invested' column for Consumer Stapl
for stock_name in stock_names_con:
    day_8_col = f"{stock_name}-day-8"
    day_21_col = f"{stock_name}-day-21"
    invested_col = f"{stock_name}-invested"
    moving_averages_con[invested_col] = np.where(moving_averages_con[day_8_col] > moving_av

# Iterate over each stock and create the corresponding 'invested' column for Energy Sector
for stock_name in stock_names_energy:
    day_8_col = f"{stock_name}-day-8"
    day_21_col = f"{stock_name}-day-21"
    invested_col = f"{stock_name}-invested"
    moving_averages_energy[invested_col] = np.where(moving_averages_energy[day_8_col] > mov

# Iterate over each stock and create the corresponding 'invested' column for Financials Sec
for stock_name in stock_names_fin:
    day_8_col = f"{stock_name}-day-8"
    day_21_col = f"{stock_name}-day-21"
    invested_col = f"{stock_name}-invested"
    moving_averages_fin[invested_col] = np.where(moving_averages_fin[day_8_col] > moving_av
```

2.5 - Signal Column

Now we make a column called 'signal' which tells us when to enter and leave the market based on the momentum trading strategy. We want to buy when the trend is changing and flips.

A value of +1 indicates that we should buy, and a value of -1 indicates that we should sell.

```
#Signal column indicator

for stock_name in stock_names_con:
    invested_col = f"{stock_name}-invested"
    signal = f"{stock_name}-signal"

    moving_averages_con[signal] = moving_averages_con[invested_col].diff()
    moving_averages_con.at[moving_averages_con.index[0], signal] = 1.0  # Set NaN in the fi

# Display the modified DataFrame with the 'signal' columns

for stock_name in stock_names_energy:
    invested_col = f"{stock_name}-invested"
    signal = f"{stock_name}-signal"

    moving_averages_energy[signal] = moving_averages_energy[invested_col].diff()
    moving_averages_energy.at[moving_averages_energy.index[0], signal] = 1.0  # Set NaN in 

# Display the modified DataFrame with the 'signal' columns

for stock_name in stock_names_fin:
    invested_col = f"{stock_name}-invested"
    signal = f"{stock_name}-signal"

    moving_averages_fin[signal] = moving_averages_fin[invested_col].diff()
    moving_averages_fin.at[moving_averages_con.index[0], signal] = 1.0  # Set NaN in the fi

# Display the modified DataFrames with the 'signal' columns (only needed for validation)
#print(moving_averages_con.head(10))
# print(moving_averages_energy.head(10))
# print(moving_averages_fin.head(10))
```

2.6 - System Returns

In this section we get the true returns of each stock using momentum trading strategy. This combines the returns with the invested column to allow us to determine overall returns and compare with others.

```
##System Returns with Momentum Trading

# Iterate over each stock and calculate the corresponding 'system_return' column
stock_names_con = set(col.split('-')[0] for col in moving_averages_con.columns)
for stock_name in stock_names_con:
    return_col = f"{stock_name}-return"
    invested_col = f"{stock_name}-invested"
    system_return_col = f"{stock_name}-system_return"

    # Calculate the 'system_return' column
    moving_averages_con[system_return_col] = moving_averages_con[invested_col] * moving_ave

for stock_name in stock_names_energy:
    return_col = f"{stock_name}-return"
    invested_col = f"{stock_name}-invested"
    system_return_col = f"{stock_name}-system_return"

    # Calculate the 'system_return' column
    moving_averages_energy[system_return_col] = moving_averages_energy[invested_col] * movi

for stock_name in stock_names_fin:
    return_col = f"{stock_name}-return"
    invested_col = f"{stock_name}-invested"
    system_return_col = f"{stock_name}-system_return"

    # Calculate the 'system_return' column
    moving_averages_fin[system_return_col] = moving_averages_fin[invested_col] * moving_ave


 #Display the modified moving_averages DataFrame with the 'system_return' columns
print("Consumer Staples:")
print(moving_averages_con.filter(regex='-system_return'))

# Display the data frame for Energy
print("\nEnergy:")
print(moving_averages_energy.filter(regex='-system_return'))

# Display the data frame for Financials
print("\nFinancials:")
print(moving_averages_fin.filter(regex='-system_return'))
```

```
Consumer Staples:
            SYY-system_return  CL-system_return  COST-system_return  \
2021-01-04          -0.000000         -0.000000            0.000000
2021-01-05           0.000000          0.000000           -0.000000
2021-01-06           0.000000         -0.000000           -0.015340
2021-01-07           0.000000         -0.000000           -0.005691
2021-01-08           0.000000          0.000000            0.005475
...                       ...               ...                 ...
2021-12-23           0.018168          0.003994            0.001273
2021-12-27           0.011157          0.013438            0.023523
```

```
2021-12-28          0.010396          0.006533            0.002074
2021-12-29         -0.004864          0.005314            0.005528
2021-12-30          0.000770         -0.003776           -0.006822

            PEP-system_return  EL-system_return  MO-system_return  \
2021-01-04         -0.027551         -0.042986         -0.003910
2021-01-05          0.002976          0.014947         -0.000000
2021-01-06         -0.012308         -0.001895          0.000000
2021-01-07         -0.003223         -0.000271          0.000000
2021-01-08          0.011931          0.009480         -0.000000
...                      ...               ...               ...
2021-12-23         -0.001119          0.011791         -0.003847
2021-12-27          0.009905          0.008922          0.001925
2021-12-28          0.005177         -0.003989          0.012531
2021-12-29          0.003533          0.006180          0.000422
2021-12-30         -0.001736         -0.007431         -0.003170

            DLTR-system_return  PG-system_return  CLX-system_return  \
2021-01-04                -0.0         -0.009532          -0.007357
2021-01-05                 0.0          0.006365          -0.000000
2021-01-06                 0.0          0.010471          -0.000000
2021-01-07                 0.0         -0.009390          -0.000000
2021-01-08                -0.0         -0.000432           0.000000
...                        ...               ...                ...
2021-12-23                 0.0          0.004884          -0.005520
2021-12-27                 0.0          0.011612           0.006222
2021-12-28                 0.0          0.005357           0.006067
2021-12-29                 0.0          0.008256          -0.003204
2021-12-30                 0.0         -0.008686           0.005470

            WMT-system_return
2021-01-04          0.000000
2021-01-05         -0.000000
2021-01-06          0.000000
2021-01-07         -0.000000
2021-01-08         -0.000000
...                      ...
2021-12-23         -0.002220
2021-12-27          0.009063
2021-12-28          0.014249
2021-12-29         -0.000490
2021-12-30          0.003218

[251 rows x 10 columns]

Energy:
            CTRA-system_return  XOM-system_return  OKE-system_return  \
2021-01-04                 0.0                0.0               -0.0
```

2.7 - Performance of Momentum Trading For Each Stock

In this section we are consolidating all of the returns for each stock and organizing each sector from greatest returns to least. This will help in determining which stocks to carry onto other sections. As an example, if we invested 1 dollar, a 1.5 return means we earned out dollar back as well as 50 cents on top of our initial dollar.

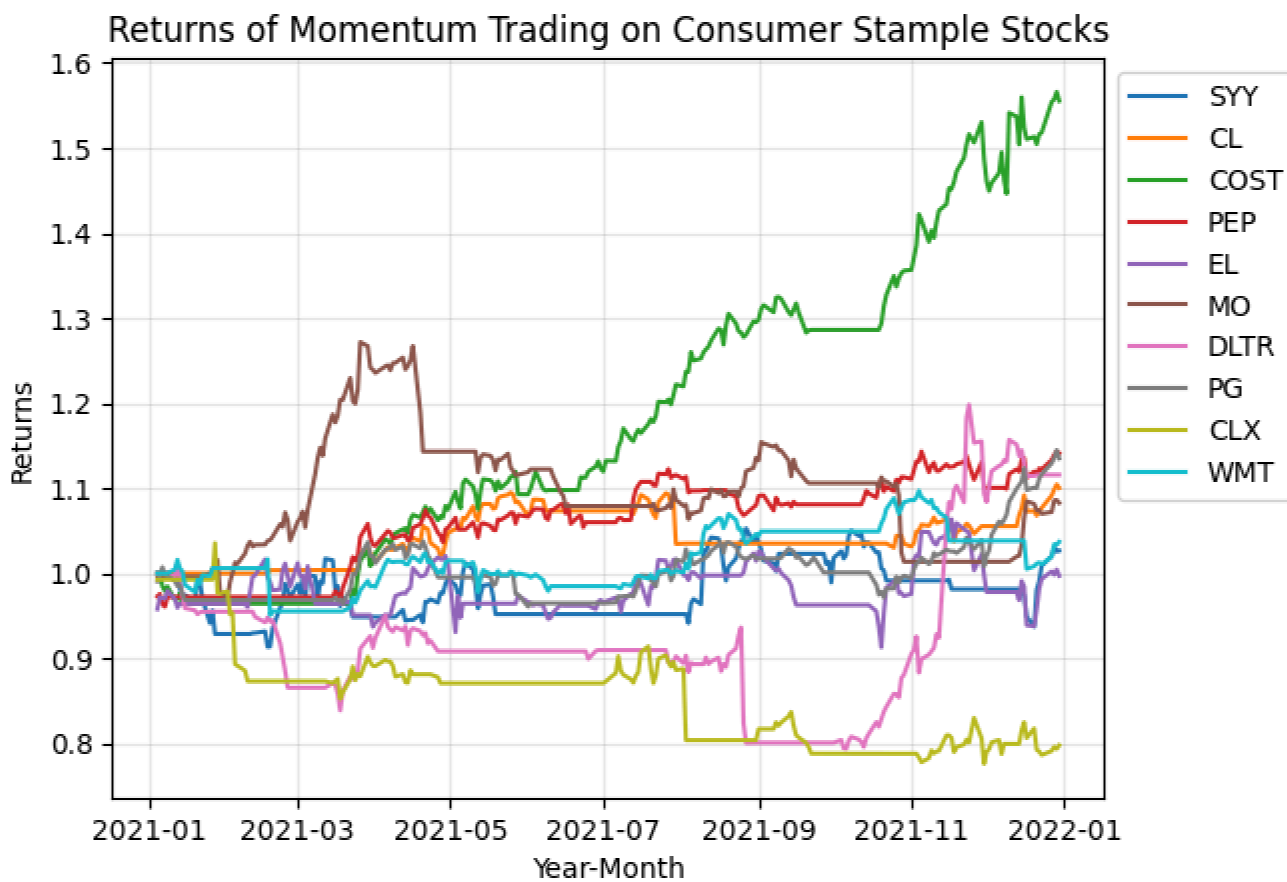
```
total_returns_con = {}
total_returns_energy = {}
total_returns_fin = {}

for stock_name in stock_names_con:
    system_return_col = f"{stock_name}-system_return"

    # Calculate the total return for each stock for Consumer Staple
    total_return = np.exp(np.sum(moving_averages_con[system_return_col]))
    total_returns_con[stock_name] = total_return

# Display the total returns for each stock in descending order
sorted_total_returns_con = sorted(total_returns_con.items(), key=lambda x: x[1], reverse=Tr
print("CONSUMER STAPLES SECTOR")
for stock_name, total_return in sorted_total_returns_con:
    print(f"Stock: {stock_name}, Total Return: {total_return:.4f}")

print('--------------------')
print("ENERGY SECTOR")
for stock_name in stock_names_energy:
    system_return_col = f"{stock_name}-system_return"

    # Calculate the total return for each stock for Energy
    total_return = np.exp(np.sum(moving_averages_energy[system_return_col]))
    total_returns_energy[stock_name] = total_return

# Display the total returns for each stock in descending order
sorted_total_returns_energy = sorted(total_returns_energy.items(), key=lambda x: x[1], reve
for stock_name, total_return in sorted_total_returns_energy:
    print(f"Stock: {stock_name}, Total Return: {total_return:.4f}")

print('--------------------')
print("FINANCIAL SECTOR")

for stock_name in stock_names_fin:
    system_return_col = f"{stock_name}-system_return"

    # Calculate the total return for each stock for Financial
    total_return = np.exp(np.sum(moving_averages_fin[system_return_col]))
    total_returns_fin[stock_name] = total_return

# Display the total returns for each stock in descending order
sorted_total_returns_fin = sorted(total_returns_fin.items(), key=lambda x: x[1], reverse=Tr
for stock_name, total_return in sorted_total_returns_fin:
    print(f"Stock: {stock_name}, Total Return: {total_return:.4f}")
```

```
CONSUMER STAPLES SECTOR
Stock: COST, Total Return: 1.5553
Stock: PEP, Total Return: 1.1412
Stock: PG, Total Return: 1.1350
Stock: DLTR, Total Return: 1.1158
Stock: CL, Total Return: 1.1003
Stock: MO, Total Return: 1.0826
Stock: WMT, Total Return: 1.0371
Stock: SYY, Total Return: 1.0265
Stock: EL, Total Return: 0.9970
Stock: CLX, Total Return: 0.7979
--------------------
ENERGY SECTOR
Stock: DVN, Total Return: 1.8499
Stock: FANG, Total Return: 1.7452
Stock: OKE, Total Return: 1.2890
Stock: HES, Total Return: 1.2793
Stock: WMB, Total Return: 1.2591
Stock: APA, Total Return: 1.1639
Stock: XOM, Total Return: 1.1181
Stock: PSX, Total Return: 1.0855
Stock: VLO, Total Return: 1.0263
Stock: CTRA, Total Return: 0.7502
--------------------
FINANCIAL SECTOR
Stock: WFC, Total Return: 1.4227
Stock: PRU, Total Return: 1.3178
Stock: KEY, Total Return: 1.2884
Stock: IVZ, Total Return: 1.2158
Stock: GS, Total Return: 1.1974
Stock: SPGI, Total Return: 1.1836
Stock: JPM, Total Return: 1.1325
Stock: V, Total Return: 0.9503
Stock: DFS, Total Return: 0.9150
Stock: MA, Total Return: 0.8686
```

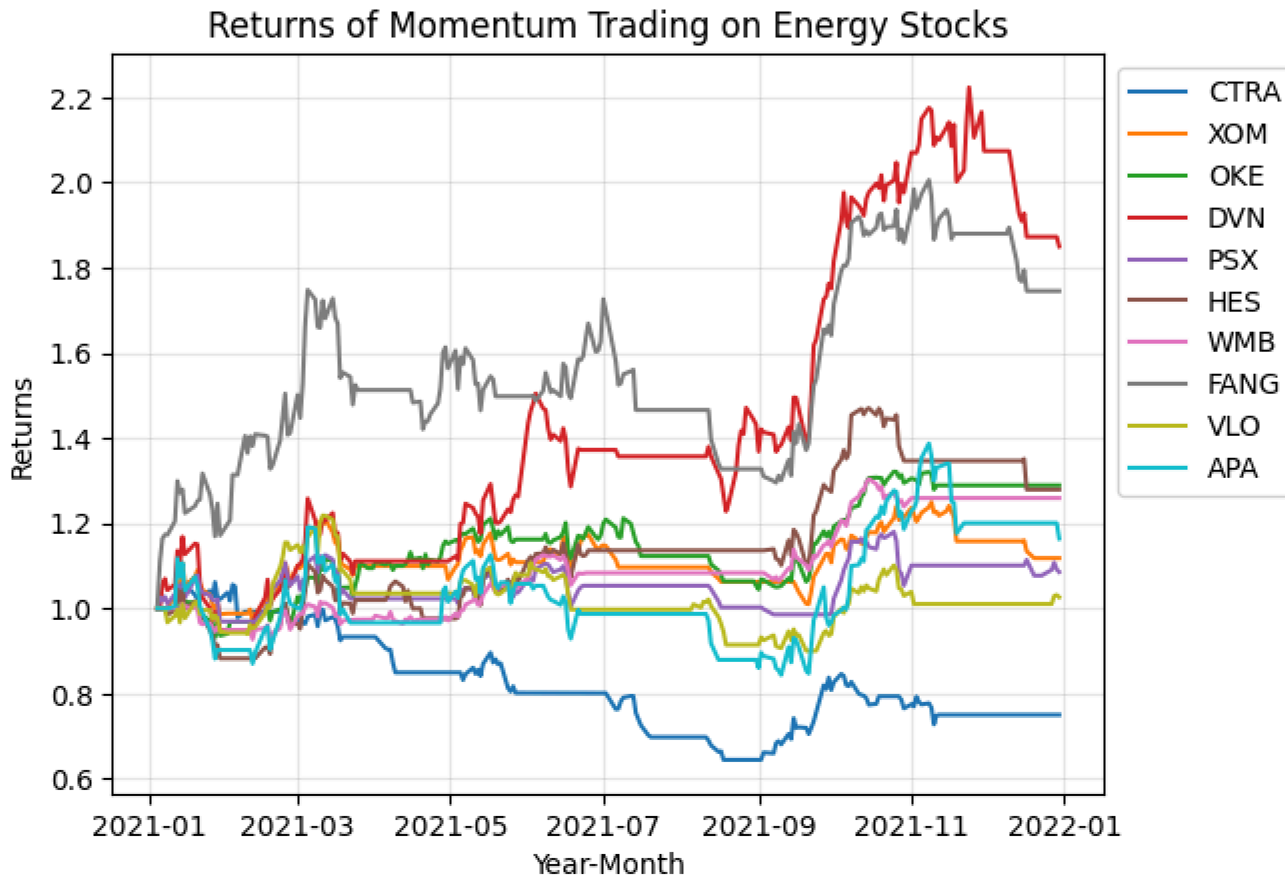
2.8 - Plots to show Performance of Each Stock in Each Sector

Below will show 3 graphs (1 per sector) with all 10 stocks displayed to illustrate the highest returns. This will also allow us to see how the investment in each stock changed over time (2021)

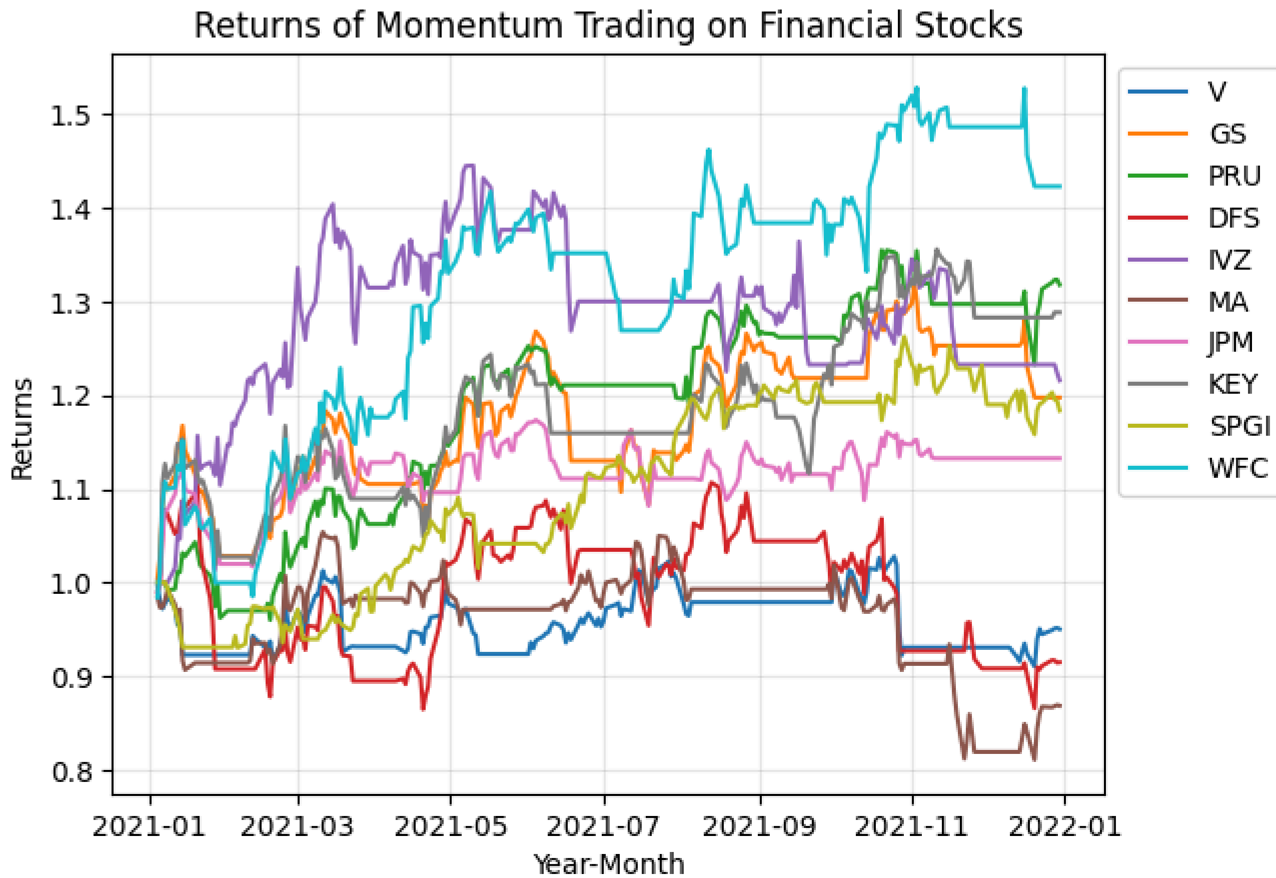
```
#Graph for Consumer Staples Momentum Trading
for stock_name in stock_names_con:

  plt.plot(np.exp(moving_averages_con[f"{stock_name}-system_return"]).cumprod(),label=stock_
  plt.legend(bbox_to_anchor=(1.0, 1.0))
  plt.title("Returns of Momentum Trading on Consumer Stample Stocks")
  plt.xlabel("Year-Month")
  plt.ylabel("Returns")
  plt.grid(True, alpha=0.3)
```




```
#Graph for Consumer Energy Trading
for stock_name in stock_names_energy:
  plt.plot(np.exp(moving_averages_energy[f"{stock_name}-system_return"]).cumprod(),label=st
  plt.legend(bbox_to_anchor=(1.0, 1.0))
  plt.title("Returns of Momentum Trading on Energy Stocks")
  plt.xlabel("Year-Month")
  plt.ylabel("Returns")
  plt.grid(True, alpha=0.3)
```




```
#Graph for Financial Momentum Trading
for stock_name in stock_names_fin:
  plt.plot(np.exp(moving_averages_fin[f"{stock_name}-system_return"]).cumprod(),label=stock_
  plt.legend(bbox_to_anchor=(1.0, 1.0))
  plt.title("Returns of Momentum Trading on Financial Stocks")
  plt.xlabel("Year-Month")
  plt.ylabel("Returns")
  plt.grid(True, alpha=0.3)
```



As you can see in the plots above, as expected, the 3 selected stocks based on the 8-21 Momentum Trading Strategy all have the highest returns shown in 2021. Note here there are some horizontal (or flat) lines here indicating times where returns stayed same as these are times we are not invested in the stock.

2.9 - Discussion

In the Consumer Staples sector COSTCO ('COST'), Pespi ('PEP'), and Procter & Gamble ('PG') has the highest returns using the Momentum Trading Strategy.

In the Energy sector Devon Energy ('DVN'), Hess ('HES'), and Diamondback Energy ('FANG') has the highest returns using the Momentum Trading Strategy.

In the Energy sector Wells Fargo ('WFC'), Prudential Financial ('PRU'), and S&P Global ('SPGI') has the highest returns using the Momentum Trading Strategy.

In the Consumer staple sector, Costco really performed much better than the others where alot hovered around break even point.

In the energy sector, there were very well performing stocks using momentum trading strategy. DVN and FANG had excellent returns (and similar trading movements) while a good amount of the sector performed between 1.3 and 1.1 return which is still making money!

In the financial sector, we had a much larger variation in returns than the other sectors but still 7 out of the 10 stocks made money using the momentum trading strategy.

3 - Optimization Model

We have selected 9 stocks out of 30. Three best performing from each sector are picked for our next steps

Top 9 stocks from respective sectors:

Consumer staples sector

1. Cost (Costco Wholesale Corporation)
2. PEP (PepsiCo, Inc.)
3. PG (Procter & Gamble Co)

Energy sector

1. DVN (Devon Energy Corp)
2. FANG (Diamondback Energy Inc)
3. Hes (Hess Corp.)

Financials sector

1. WFC(Wells Fargo & Co)
2. SPGI(S&P Global Inc)
3. Pru(Prudential Financial Inc)

```
# Defining selected stocks for each sector.
selected_stocks_con = ['COST', 'PEP', 'PG']
selected_stocks_energy = ['DVN', 'HES', 'FANG']
selected_stocks_fin = ['WFC', 'PRU', 'SPGI']

# Extracting return data for the selected stocks in each sector.
selected_stocks_con_data = return_con_data[selected_stocks_con]
selected_stocks_energy_data = return_energy_data[selected_stocks_energy]
selected_stocks_fin_data = return_fin_data[selected_stocks_fin]

# Combining data for selected stocks from all sectors into 'Top_Stocks'.
Top_Stocks = pd.concat([selected_stocks_con_data, selected_stocks_energy_data, selected_sto

# Displaying the combined DataFrame 'Top_Stocks'.
print(Top_Stocks)
```

```
                COST       PEP        PG       DVN       HES      FANG  \
2017-01-04  0.000188  0.001911  0.003564  0.008921 -0.014168  0.003099
2017-01-05  0.019717 -0.001335  0.006627  0.031789  0.002745  0.000965
2017-01-06 -0.000491 -0.001433 -0.000352 -0.006937 -0.003221 -0.000096
2017-01-09 -0.011423 -0.010520 -0.007409 -0.042942 -0.020840 -0.021513
2017-01-10  0.004287 -0.014402 -0.010782  0.002576  0.013859  0.012620
...              ...       ...       ...       ...       ...       ...
2021-12-23  0.001274 -0.001118  0.004896 -0.005675 -0.008366  0.002365
2021-12-27  0.023802  0.009954  0.011680  0.060880  0.028848  0.049084
2021-12-28  0.002076  0.005190  0.005371 -0.002466 -0.004365 -0.008818
2021-12-29  0.005543  0.003539  0.008290 -0.006742 -0.008103 -0.013163
2021-12-30 -0.006798 -0.001734 -0.008648 -0.011991 -0.009508 -0.012878

                 WFC       PRU      SPGI
2017-01-04  0.000893  0.012207  0.030907
2017-01-05 -0.015522 -0.014980  0.007607
2017-01-06 -0.002537  0.005739  0.017852
2017-01-09 -0.014535 -0.003899 -0.011518
2017-01-10  0.007006  0.007924 -0.017038
...              ...       ...       ...
2021-12-23  0.006871  0.012534  0.001014
2021-12-27  0.008478  0.005358  0.009203
2021-12-28 -0.007177  0.002114 -0.006275
2021-12-29  0.000620  0.000183 -0.001158
2021-12-30 -0.007224 -0.004125 -0.008576

[1257 rows x 9 columns]
```

Calculating and printing the Average Return and Standard Deviation of daily returns for the 9 stocks we picked in the beginning of this section from all three sectors.

```
# Calculating and displaying the average return for each stock in 'Top_Stocks'.
Avg_Return = pd.DataFrame(np.mean(Top_Stocks) ,columns=["Avg_Return"])
print(Avg_Return)
# Calculating and displaying the standard deviation of returns for each stock in 'Top_Stock
Std_Dev_Return = pd.DataFrame(np.std(Top_Stocks) ,columns=["Std_Dev_Return"])
print(Std_Dev_Return)
```

```
      Avg_Return
COST    0.001186
PEP     0.000602
PG      0.000718
DVN     0.000723
HES     0.000691
FANG    0.000803
WFC     0.000243
PRU     0.000473
SPGI    0.001357
      Std_Dev_Return
COST        0.013570
PEP         0.013162
PG          0.012680
DVN         0.036061
HES         0.030956
FANG        0.037155
WFC         0.022109
PRU         0.023206
SPGI        0.017280
/usr/local/lib/python3.10/dist-packages/numpy/core/fromnumeric.py:3430: FutureWarning:
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```

Covariance Matrix is a guide that shows how different stocks in a group behave together. If the number is positive, it means those stocks usually move in the same direction—either up or down. If it's negative, they tend to move in opposite directions.

```
# Calculating and displaying the covariance matrix for the stocks in 'Top_Stocks'.
Covariance_matrix = Top_Stocks.cov()
Covariance_matrix
```

	COST	PEP	PG	DVN	HES	FANG	WFC	PRU	S
COST	0.000184	0.000096	0.000083	0.000082	0.000077	0.000049	0.000087	0.000096	0.000
PEP	0.000096	0.000173	0.000123	0.000110	0.000101	0.000080	0.000123	0.000141	0.000
PG	0.000083	0.000123	0.000161	0.000081	0.000090	0.000053	0.000100	0.000118	0.000
DVN	0.000082	0.000110	0.000081	0.001301	0.000895	0.001119	0.000432	0.000486	0.000
HES	0.000077	0.000101	0.000090	0.000895	0.000959	0.000883	0.000379	0.000445	0.000
FANG	0.000049	0.000080	0.000053	0.001119	0.000883	0.001382	0.000402	0.000473	0.000
WFC	0.000087	0.000123	0.000100	0.000432	0.000379	0.000402	0.000489	0.000413	0.000
PRU	0.000096	0.000141	0.000118	0.000486	0.000445	0.000473	0.000413	0.000539	0.000
SPGI	0.000105	0.000116	0.000099	0.000226	0.000196	0.000208	0.000181	0.000208	0.000

Considering the covariance between COST and PG (0.000083) compared to COST and WFC (0.000087), for instance. The slightly higher covariance between COST and WFC suggests they might share a bit more common ground in terms of returns, possibly impacting risk differently than COST and PG, making for an interesting consideration in portfolio diversification.

Correlation Matrix is like a compatibility scale for stocks. If the number is positive, it means that the stocks have good synergy, moving in similar directions. If it's negative, they're a bit like contrasts. A number close to 1 means they have strong compatibility, and close to -1 means there's a bit of complexity. It's like having a mix of closely aligned and more independent stocks.

```
# Calculating and displaying the correlation matrix for the stocks in 'Top_Stocks'.
Corr_matrix = Top_Stocks.corr()
Corr_matrix
```

	COST	PEP	PG	DVN	HES	FANG	WFC	PRU	S
COST	1.000000	0.534858	0.481019	0.168237	0.184205	0.096903	0.289120	0.304957	0.447
PEP	0.534858	1.000000	0.735452	0.231088	0.248441	0.163246	0.421384	0.461259	0.509
PG	0.481019	0.735452	1.000000	0.177020	0.229820	0.111384	0.355585	0.399041	0.452
DVN	0.168237	0.231088	0.177020	1.000000	0.801109	0.834363	0.541752	0.580743	0.362
HES	0.184205	0.248441	0.229820	0.801109	1.000000	0.766843	0.552890	0.619014	0.365
FANG	0.096903	0.163246	0.111384	0.834363	0.766843	1.000000	0.488899	0.548378	0.324
WFC	0.289120	0.421384	0.355585	0.541752	0.552890	0.488899	1.000000	0.805143	0.472
PRU	0.304957	0.461259	0.399041	0.580743	0.619014	0.548378	0.805143	1.000000	0.517
SPGI	0.447568	0.509128	0.452492	0.362237	0.365604	0.324224	0.472257	0.517779	1.000

The correlation between COST and PG (0.481019) is less intense than that between COST and WFC (0.289121). This suggests that COST and PG move somewhat in sync, but COST and WFC have a weaker association, indicating potential diversification benefits by including both in a portfolio for a balanced risk approach.

3.1 - Nonlinear optimization model

```
# Calculating and displaying the covariance matrix for the stocks in 'Top_Stocks'.
df_cov = Top_Stocks.cov()
# print('Covariance Matrix:')
# print(df_cov)
# Adding a blank line for better readability.
print('\n')

# Calculating and displaying the average return for each stock in 'Top_Stocks'.
df_return = Top_Stocks.mean()
print('Average Return:')
print(df_return)
```

```
Average Return:
COST    0.001186
PEP     0.000602
PG      0.000718
DVN     0.000723
HES     0.000691
FANG    0.000803
WFC     0.000243
PRU     0.000473
```

```
SPGI    0.001357
dtype: float64
```

```
# Importing necessary classes and functions from 'pyomo'.
from pyomo.environ import *

# Defining the list of top stocks.
top_stocks = ['COST', 'PEP', 'PG', 'DVN', 'FANG', 'HES', 'WFC', 'SPGI', 'PRU']

# Creating a concrete model in Pyomo.
m = ConcreteModel()

# Adding decision variables for each stock with constraints using loop.
for stock in top_stocks:
    m.add_component(stock, Var(within=NonNegativeReals, bounds=(0, 1)))



# Declaring the objective function to maximize returns.
m.objective = Objective(expr = sum(getattr(m, stock) * return_val for stock, return_val in
                        sense=maximize)

# Declaring constraints:
# 1. Sum of all proportions should equal 1.
m.sum_proportions = Constraint(expr = sum(getattr(m, stock) for stock in top_stocks) == 1)

# 2. Set maximum risk
m.total_risk = Constraint(expr = sum(getattr(m, stock) for stock in top_stocks) >= 0.0)
```

```
<ipython-input-41-ab939aa9b15d>:2: DeprecationWarning: Calling np.sum(generator) is dep
  m.objective = Objective(expr = sum(getattr(m, stock) * return_val for stock, return_v
<ipython-input-41-ab939aa9b15d>:7: DeprecationWarning: Calling np.sum(generator) is dep
  m.sum_proportions = Constraint(expr = sum(getattr(m, stock) for stock in top_stocks)
<ipython-input-41-ab939aa9b15d>:10: DeprecationWarning: Calling np.sum(generator) is de
  m.total_risk = Constraint(expr = sum(getattr(m, stock) for stock in top_stocks) >= 0.
```

```
#  Calculate risk
def calc_risk(m):
    variables = [getattr(m, stock) for stock in top_stocks]
    risk_exp = 0
    for i in range(len(variables)):
        for j in range(len(variables)):
            risk_exp += variables[i] * df_cov.at[top_stocks[i], top_stocks[j]] * variables[
    return risk_exp

# We are going to use this expression to compute the risk
m.risk_expression = Expression(rule=calc_risk)

# 3. Set maximum risk
max_risk = 0.0006
# Sequence of risk levels
risk_limits = np.arange(0.0001, max_risk, 0.000004)
risk_limits
# # Remove the existing total_risk constraint if it already exists
# try:
#     del m.total_risk
# except AttributeError:
#     pass

# m.total_risk = Constraint(expr=m.risk_expression <= max_risk)
```

```
array([0.0001  , 0.000104, 0.000108, 0.000112, 0.000116, 0.00012 ,
       0.000124, 0.000128, 0.000132, 0.000136, 0.00014 , 0.000144,
       0.000148, 0.000152, 0.000156, 0.00016 , 0.000164, 0.000168,
       0.000172, 0.000176, 0.00018 , 0.000184, 0.000188, 0.000192,
       0.000196, 0.0002  , 0.000204, 0.000208, 0.000212, 0.000216,
       0.00022 , 0.000224, 0.000228, 0.000232, 0.000236, 0.00024 ,
       0.000244, 0.000248, 0.000252, 0.000256, 0.00026 , 0.000264,
       0.000268, 0.000272, 0.000276, 0.00028 , 0.000284, 0.000288,
       0.000292, 0.000296, 0.0003  , 0.000304, 0.000308, 0.000312,
       0.000316, 0.00032 , 0.000324, 0.000328, 0.000332, 0.000336,
       0.00034 , 0.000344, 0.000348, 0.000352, 0.000356, 0.00036 ,
       0.000364, 0.000368, 0.000372, 0.000376, 0.00038 , 0.000384,
       0.000388, 0.000392, 0.000396, 0.0004  , 0.000404, 0.000408,
       0.000412, 0.000416, 0.00042 , 0.000424, 0.000428, 0.000432,
       0.000436, 0.00044 , 0.000444, 0.000448, 0.000452, 0.000456,
       0.00046 , 0.000464, 0.000468, 0.000472, 0.000476, 0.00048 ,
       0.000484, 0.000488, 0.000492, 0.000496, 0.0005  , 0.000504,
       0.000508, 0.000512, 0.000516, 0.00052 , 0.000524, 0.000528,
       0.000532, 0.000536, 0.00054 , 0.000544, 0.000548, 0.000552,
       0.000556, 0.00056 , 0.000564, 0.000568, 0.000572, 0.000576,
       0.00058 , 0.000584, 0.000588, 0.000592, 0.000596])
```

```
print(len(risk_limits))
```

```
125
```

3.2 - Removal of Infeasible Solutions:

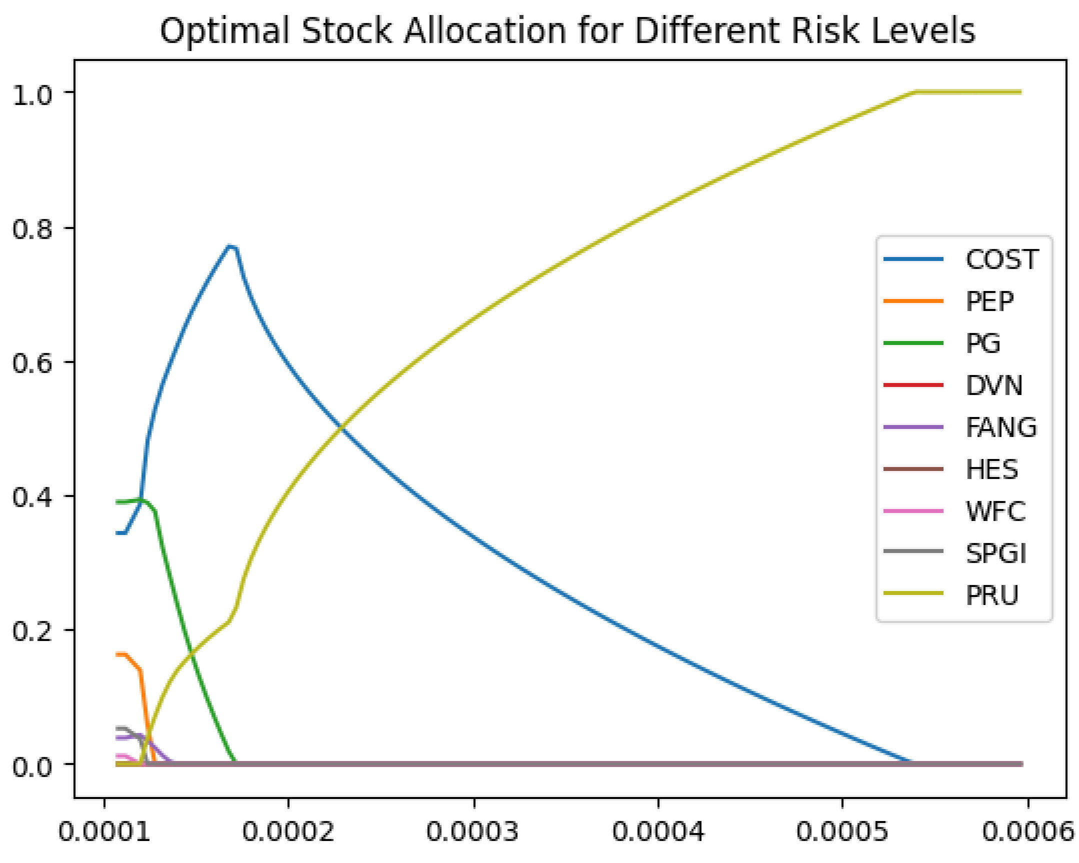
```
# Importing necessary classes and functions from 'pyomo'.

from pyomo.opt import SolverFactory, TerminationCondition

# Assume 'm' is already defined and has the necessary components (vars, constraints, etc.)
# Also, 'risk_limits' is defined before this code chunk.


# Updating risk constraint for each limit and then solving the problem
param_analysis = {}  # key=risk, value=stock allocations
returns = {}  # key=risk, value=return

for r in risk_limits:
    # Remove constraint to avoid error messages
    m.del_component(m.total_risk)
    m.total_risk = Constraint(expr=m.risk_expression <= r)

    # Run solver
    result = SolverFactory('ipopt', executable=ipopt_executable).solve(m)

    # If solution is not feasible, ignore this run
    if result.solver.termination_condition == TerminationCondition.infeasible:
        continue

    # Store our allocation proportions
    param_analysis[r] = [getattr(m, stock)() for stock in top_stocks]

    # Store our returns
    returns[r] = sum(getattr(m, stock)() * return_val for stock, return_val in zip(top_stoc
```

```
WARNING:pyomo.core:Loading a SolverResults object with a warning status into model.name
  - termination condition: infeasible
  - message from solver: Ipopt 3.12.13\x3a Converged to a locally infeasible point. Pro
WARNING:pyomo.core:Loading a SolverResults object with a warning status into model.name
  - termination condition: infeasible
  - message from solver: Ipopt 3.12.13\x3a Converged to a locally infeasible point. Pro
WARNING:pyomo.core:Loading a SolverResults object with a warning status into model.name
  - termination condition: maxIterations
  - message from solver: Ipopt 3.12.13\x3a Maximum Number of Iterations Exceeded.
<ipython-input-44-e6c9eb57de6a>:29: DeprecationWarning: Calling np.sum(generator) is de
  returns[r] = sum(getattr(m, stock)() * return_val for stock, return_val in zip(top_st
WARNING:pyomo.core:Loading a SolverResults object with a warning status into model.name
  - termination condition: maxIterations
  - message from solver: Ipopt 3.12.13\x3a Maximum Number of Iterations Exceeded.
WARNING:pyomo.core:Loading a SolverResults object with a warning status into model.name
  - termination condition: infeasible
  - message from solver: Ipopt 3.12.13\x3a Converged to a locally infeasible point. Pro
```

```
# Printing the dictionary to check the feasibility of solutions.
print(param_analysis)
```

```
{0.00010800000000000001: [0.3436585518427057, 0.16301434431176168, 0.38980128254970325,
```

```
# Converting the dictionary 'param_analysis' to a DataFrame and setting column names.
param_analysis = pd.DataFrame.from_dict(param_analysis, orient='index')
param_analysis.columns = ['COST', 'PEP', 'PG', 'DVN', 'FANG', 'HES', 'WFC', 'SPGI', 'PRU']
# Plotting the optimal stock allocation for different risk levels.
param_analysis.plot()
plt.title('Optimal Stock Allocation for Different Risk Levels')
plt.show()
```



Each line in the chart shows how the optimal allocation to a particular stock changes as the level of risk changes. For instance, one stock begins with a higher allocation at lower risk levels and decreases as risk increases, whereas another stock's allocation increases with the risk level. The lines intersect at various points, suggesting that the optimal allocation changes depending on the risk level. Example: DVN shows an optimal allocation at lower risks which rapidly decreases as risk increases whereas PRU has a rising allocation with increased risk.

```
# Extracting risk values from dictionary keys
risk = list(returns.keys())  # Converting dict_keys to a list
print("Risk Levels:", risk)

# Extracting reward values from dictionary values
reward = list(returns.values())  # Converting dict_values to a list
print("Reward Levels:", reward)
```

```
Risk Levels: [0.00010800000000000001, 0.00011200000000000001, 0.00012000000000000002, 0
Reward Levels: [0.0008404375025847999, 0.0008404375034620469, 0.0008727374469269797, 0.
```

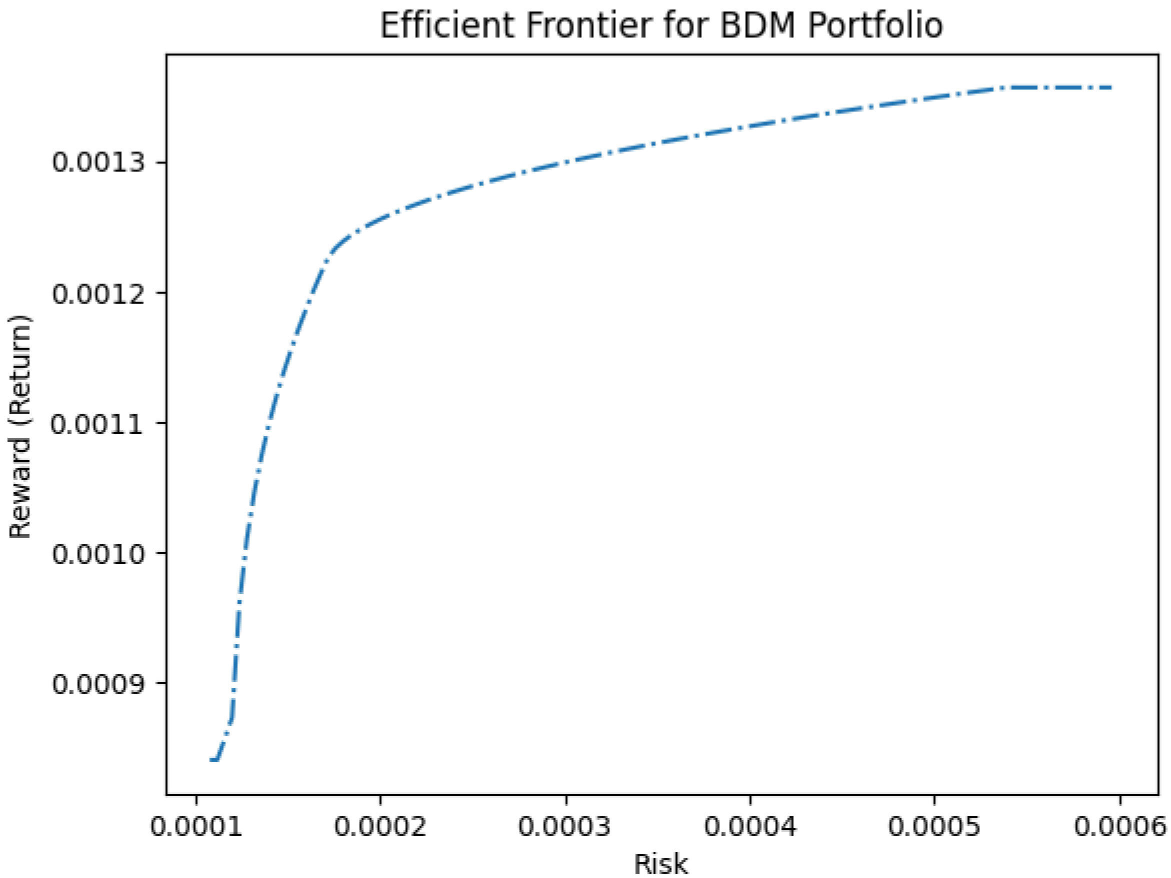
```
# Print the keys of the DataFrame
print("Keys of the DataFrame:")
print(param_analysis.keys())

# Print the head of the DataFrame (first 30 rows)
print("\nHead of the DataFrame (First 30 rows):")
print(param_analysis.head(30))
```

```
Keys of the DataFrame:
Index(['COST', 'PEP', 'PG', 'DVN', 'FANG', 'HES', 'WFC', 'SPGI', 'PRU'], dtype='obje

Head of the DataFrame (First 30 rows):
              COST       PEP        PG       DVN      FANG       HES  \
0.000108  0.343659  0.163014  0.389801  0.000000  0.038790  0.000000
0.000112  0.343659  0.163014  0.389801  0.000000  0.038790  0.000000
0.000120  0.386817  0.139519  0.393307  0.000001  0.043191  0.000004
0.000124  0.480619  0.056711  0.388694  0.000004  0.034570  0.000013
0.000128  0.527879  0.001103  0.375924  0.000006  0.024219  0.000012
0.000132  0.564627  0.000039  0.323162  0.000007  0.012905  0.000016
0.000136  0.594022  0.000022  0.280108  0.000007  0.003830  0.000014
0.000140  0.622296  0.000018  0.238361  0.000007  0.000072  0.000013
0.000144  0.649402  0.000016  0.198108  0.000006  0.000019  0.000011
0.000148  0.673641  0.000015  0.162107  0.000006  0.000019  0.000010
0.000152  0.695740  0.000014  0.129287  0.000006  0.000012  0.000009
0.000156  0.716187  0.000013  0.098917  0.000006  0.000010  0.000009
0.000160  0.735304  0.000013  0.070522  0.000005  0.000009  0.000008
0.000164  0.753320  0.000012  0.043761  0.000005  0.000008  0.000008
0.000168  0.770414  0.000004  0.018391  0.000002  0.000003  0.000003
0.000172  0.767117  0.000008  0.000022  0.000005  0.000006  0.000007
0.000176  0.724438  0.000006  0.000010  0.000004  0.000005  0.000006
0.000180  0.694223  0.000005  0.000008  0.000004  0.000005  0.000005
0.000184  0.669465  0.000005  0.000007  0.000004  0.000004  0.000005
0.000188  0.647972  0.000005  0.000007  0.000004  0.000004  0.000005
0.000192  0.628709  0.000005  0.000007  0.000006  0.000006  0.000007
0.000196  0.611123  0.000005  0.000006  0.000004  0.000004  0.000005
0.000200  0.594818  0.000005  0.000006  0.000004  0.000004  0.000005
0.000204  0.579556  0.000005  0.000006  0.000004  0.000004  0.000005
0.000208  0.565159  0.000005  0.000006  0.000004  0.000004  0.000005
```

```
0.000212  0.551495  0.000005  0.000006  0.000004  0.000004  0.000005
0.000216  0.538462  0.000005  0.000006  0.000004  0.000004  0.000005
0.000220  0.525980  0.000004  0.000006  0.000004  0.000004  0.000005
0.000224  0.513985  0.000004  0.000006  0.000004  0.000004  0.000005
0.000228  0.502423  0.000004  0.000006  0.000004  0.000004  0.000005

               WFC      SPGI       PRU
0.000108  0.011911  0.052824  0.000000
0.000112  0.011911  0.052824  0.000000
0.000120  0.000059  0.037098  0.000004
0.000124  0.000005  0.000048  0.039336
0.000128  0.000004  0.000012  0.070841
0.000132  0.000003  0.000008  0.099232
0.000136  0.000003  0.000007  0.121986
0.000140  0.000003  0.000007  0.139224
0.000144  0.000003  0.000006  0.152429
0.000148  0.000003  0.000006  0.164192
0.000152  0.000003  0.000006  0.174924
0.000156  0.000003  0.000006  0.184850
0.000160  0.000003  0.000005  0.194130
0.000164  0.000003  0.000005  0.202877
0.000168  0.000001  0.000002  0.211180
0.000172  0.000003  0.000005  0.232828
0.000176  0.000003  0.000004  0.275525
0.000180  0.000002  0.000004  0.305743
0.000184  0.000002  0.000004  0.330503
0.000188  0.000002  0.000004  0.351996
```

3.3 - Efficent frontier

```
# Import necessary modules from the pylab library
from pylab import *

# Create a line plot of risk vs. reward using the efficient frontier data
plot(risk, reward, '-.')

# Set the title of the plot
title('Efficient Frontier for BDM Portfolio')

# Label the x-axis as 'Risk' and the y-axis as 'Reward (Return)'
xlabel('Risk')
ylabel('Reward (Return)')

# Display the plot
plt.show()
```



- At a low level of risk, approximately 0.00025, the portfolio's expected return is slightly above 0.0012. This indicates that for this portfolio, even a marginal increase in risk from the minimum risk level can result in a substantial increase in expected return.
- As we move rightward along the x-axis to a risk level of about 0.00030, the graph shows the expected return increasing to nearly 0.0014. This further supports the principle that within certain ranges, taking on additional risk is associated with higher potential returns
- The plateau effect on the curve beyond the risk level of 0.00050 exemplifies the concept of diminishing marginal returns to risk. It suggests that there is a threshold beyond which the portfolio's risk-return trade-off becomes less attractive.

```
# Retrieve information about the index of the param_analysis DataFrame
index_info = param_analysis.index

# Print the index information
print("Index Information:", index_info)
```

```
Index Information: Float64Index([0.00010800000000000001, 0.00011200000000000001,
                0.00012000000000000002, 0.00012400000000000003,
                0.00012800000000000002,               0.000132,
                0.00013600000000000003, 0.00014000000000000004,
                0.00014400000000000003, 0.00014800000000000002,
```

```
                ...
                 0.0005600000000000003,  0.0005640000000000003,
                 0.0005680000000000003,  0.0005720000000000004,
                 0.0005760000000000003,  0.0005800000000000003,
                 0.0005840000000000003,  0.0005880000000000003,
                 0.0005920000000000003,  0.0005960000000000004],
               dtype='float64', length=122)
```

```
print(param_analysis.loc[0.00014000000000000004])
```

```
COST    0.622296
PEP     0.000018
PG      0.238361
DVN     0.000007
FANG    0.000072
HES     0.000013
WFC     0.000003
SPGI    0.000007
PRU     0.139224
Name: 0.00014000000000000004, dtype: float64
```

```
# Selecting 3 portfolios from the above risk level allocations
selection_pf=param_analysis.loc[0.00014000000000000004, ['COST', 'PG', 'PRU']]
selection_pf = pd.DataFrame({'Allocation': selection_pf})
selection_pf
```

	Allocation
COST	0.622296
PG	0.238361
PRU	0.139224

4-Analysis

4.1 - Buy-and-Hold strategy for the MPT Portfolio

```
import yfinance as yf

# Define the ticker symbols from the optimized model
ticker_list = ['COST', 'PRU', 'PG']

# Define the date range
start_date = '2022-01-01'
end_date = '2022-12-02'

# Extract historical data for each ticker
historical_data = {}  # Dictionary to store historical data for each ticker

for ticker in ticker_list:
    # Use yfinance to get historical data
    df = yf.download(ticker, start=start_date, end=end_date, interval='1mo')

    # Store the data in the dictionary
    historical_data[ticker] = df

# Display the historical data for each ticker
for ticker, df in historical_data.items():
    print(f"\nHistorical Data for Ticker {ticker}:")
    print(df)
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed

Historical Data for Ticker COST:
                  Open        High         Low       Close   Adj Close  \
Date
2022-01-01  565.030029  568.719971  469.010010  505.130005  498.001678
2022-02-01  505.000000  534.239990  482.980011  519.250000  511.922455
2022-03-01  519.460022  586.320007  511.779999  575.849976  568.584229
2022-04-01  577.380005  612.270020  529.700012  531.719971  525.010986
2022-05-01  532.229980  546.140015  406.510010  466.220001  461.086334
2022-06-01  469.380005  491.130005  443.200012  479.279999  474.002563
2022-07-01  481.179993  542.119995  478.000000  541.299988  535.339600
2022-08-01  541.419983  564.750000  520.260010  522.099976  517.242310
2022-09-01  519.719971  542.599976  463.529999  472.269989  467.875946
2022-10-01  474.500000  512.820007  449.029999  501.500000  496.834015
2022-11-01  503.700012  542.580017  474.500000  539.250000  535.197205
2022-12-01  519.140015  519.140015  450.750000  456.500000  453.069061

              Volume
Date
2022-01-01  57966700
2022-02-01  41865600
2022-03-01  59731500
2022-04-01  49744700
2022-05-01  80773600
2022-06-01  54370600
2022-07-01  46975700
```

```
2022-08-01  42247500
2022-09-01  49753100
2022-10-01  44905600
2022-11-01  40651100
2022-12-01  54987400

Historical Data for Ticker PRU:
                  Open        High         Low       Close   Adj Close  \
Date
2022-01-01  108.820000  117.959999  104.809998  111.570000  101.006790
2022-02-01  111.570000  124.220001  105.150002  111.660004  101.088264
2022-03-01  110.040001  122.290001  101.889999  118.169998  108.063812
2022-04-01  119.320000  122.540001  108.260002  108.510002   99.229958
2022-05-01  109.059998  111.800003   96.559998  106.250000   97.163246
2022-06-01  105.830002  106.800003   90.250000   95.680000   88.574112
2022-07-01   95.320000  100.800003   89.730003   99.989998   92.564003
2022-08-01   99.000000  105.720001   94.470001   95.750000   88.638901
2022-09-01   95.339996  100.480003   85.459999   85.779999   80.341751
2022-10-01   87.309998  105.769997   86.230003  105.190002   98.521210
2022-11-01  105.989998  110.959999   98.449997  108.029999  101.181160
2022-12-01  108.500000  108.809998   96.570000   99.459999   94.207764

              Volume
Date
2022-01-01  38591400
2022-02-01  44712800
2022-03-01  49625400
2022-04-01  30407900
2022-05-01  50669600
```

```
#Appending
# Create an empty DataFrame
dfm = pd.DataFrame()

# Iterate over ticker symbols
for ticker in ticker_list:
    # Extract the 'Close' column from historical data and append to dfm
    dfm[f"{ticker}_close"] = historical_data[ticker]['Close']

# Display the first few rows of the DataFrame
dfm.head()
```

Date	COST_close	PRU_close	PG_close
2022-01-01	505.130005	111.570000	160.449997
2022-02-01	519.250000	111.660004	155.889999
2022-03-01	575.849976	118.169998	152.800003
2022-04-01	531.719971	108.510002	160.550003
2022-05-01	466.220001	106.250000	147.880005

```
# Applying log to close for each ticker
for ticker in ticker_list:
    dfm[f"{ticker}_logClose"] = np.log(dfm[f"{ticker}_close"])

# Display the first few rows of the DataFrame
dfm.head()
```

Date	COST_close	PRU_close	PG_close	COST_logClose	PRU_logClose	PG_logClose
2022-01-01	505.130005	111.570000	160.449997	6.224816	4.714652	5.077982
2022-02-01	519.250000	111.660004	155.889999	6.252385	4.715459	5.049151
2022-03-01	575.849976	118.169998	152.800003	6.355847	4.772124	5.029130
2022-04-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
# Calculating returns for each stock
for ticker in ticker_list:
    dfm[f"{ticker}_return"] = dfm[f"{ticker}_logClose"].diff()

# Display the first few rows of the DataFrame
dfm.head()
```

	COST_close	PRU_close	PG_close	COST_logClose	PRU_logClose	PG_logClose	COS
Date							
2022-01-01	505.130005	111.570000	160.449997	6.224816	4.714652	5.077982	
2022-02-01	519.250000	111.660004	155.889999	6.252385	4.715459	5.049151	
2022-03-01	575.849976	118.169998	152.800003	6.355847	4.772124	5.029130	
2022-04-01	531.719971	108.510002	160.550003	6.276117	4.686842	5.078605	-
2022-05-01	466.220001	106.250000	147.880005	6.144658	4.665795	4.996401	-

```
# Making NaN values 0.0 for return columns
for ticker in ticker_list:
    dfm[f"{ticker}_return"].fillna(0.0, inplace=True)

# Display the first few rows of the DataFrame
print(dfm.head())
```

```
            COST_close   PRU_close    PG_close  COST_logClose  PRU_logClose  \
Date
2022-01-01  505.130005  111.570000  160.449997       6.224816      4.714652
2022-02-01  519.250000  111.660004  155.889999       6.252385      4.715459
2022-03-01  575.849976  118.169998  152.800003       6.355847      4.772124
2022-04-01  531.719971  108.510002  160.550003       6.276117      4.686842
2022-05-01  466.220001  106.250000  147.880005       6.144658      4.665795

            PG_logClose  COST_return  PRU_return  PG_return
Date
2022-01-01     5.077982     0.000000    0.000000   0.000000
2022-02-01     5.049151     0.027570    0.000806  -0.028832
2022-03-01     5.029130     0.103462    0.056666  -0.020021
2022-04-01     5.078605    -0.079730   -0.085282   0.049476
2022-05-01     4.996401    -0.131459   -0.021048  -0.082204
```

```
# Selecting 'return' columns for a subset DataFrame
df_log = dfm[['COST_return', 'PG_return', 'PRU_return']]

# Display the first few rows of the subset DataFrame
print(df_log.head())
```

```
            COST_return  PG_return  PRU_return
Date
2022-01-01     0.000000   0.000000    0.000000
2022-02-01     0.027570  -0.028832    0.000806
```

```
2022-03-01     0.103462  -0.020021    0.056666
2022-04-01    -0.079730   0.049476   -0.085282
2022-05-01    -0.131459  -0.082204   -0.021048
```

Calculating profit/loss for the invested amount of 100000 as recommended according to guidelines for the assessts based on the weights from their portfolio.

```
# Initial investment amount.
starting_investment = 100000
# Portfolio allocation weights for three different stocks according to output achieved afte
weights = [0.139224,0.238361, 0.622296]
# Assign initial investment values to the portfolio on a specific date, adjusted by weights
df_log.loc["2022-01-01"] =  [(i*starting_investment)-1 for i in weights]
print(df_log)
```

```
              COST_return     PG_return    PRU_return
Date
2022-01-01  13921.400000  23835.100000  62228.600000
2022-02-01      0.027570     -0.028832      0.000806
2022-03-01      0.103462     -0.020021      0.056666
2022-04-01     -0.079730      0.049476     -0.085282
2022-05-01     -0.131459     -0.082204     -0.021048
2022-06-01      0.027627     -0.028047     -0.104786
2022-07-01      0.121689     -0.034528      0.044061
2022-08-01     -0.036115     -0.007007     -0.043330
2022-09-01     -0.100308     -0.088555     -0.109955
2022-10-01      0.060053      0.064563      0.203982
2022-11-01      0.072576      0.102192      0.026641
2022-12-01     -0.166591      0.015962     -0.082653
<ipython-input-59-23d82b1a13c3>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
  df_log.loc["2022-01-01"] =  [(i*starting_investment)-1 for i in weights]
```

Calculating cumulative return till the date

```
# Calculate the compounded monthly values by sequentially multiplying the (1 + log returns)
Monthly_BH_Values = (1 + df_log).cumprod()
Monthly_BH_Values
```

Date	COST_return	PG_return	PRU_return
2022-01-01	13922.400000	23836.100000	62229.600000
2022-02-01	14306.235433	23148.864188	62279.780631
2022-03-01	15786.382943	22685.407035	65808.906593
2022-04-01	14527.731666	23807.779863	60196.598276
2022-05-01	12617.925482	21850.678640	58929.607574
2022-06-01	12966.525286	21237.825841	52754.638330
2022-07-01	14544.404321	20504.534953	55079.053393
2022-08-01	14019.139884	20360.850612	52692.503810
2022-09-01	12612.904342	18557.800423	46898.712031
2022-10-01	13370.344245	19755.952511	56465.223732
2022-11-01	14340.706042	21774.857789	57969.496427
2022-12-01	11951.679430	22122.427855	53178.119816

```
# Add a new column 'Aggregate' to store the sum of values across all stocks for each row (m
Monthly_BH_Values['Aggregate'] = Monthly_BH_Values.sum(axis=1)
Monthly_BH_Values
```

Date	COST_return	PG_return	PRU_return	Aggregate
2022-01-01	13922.400000	23836.100000	62229.600000	99988.100000
2022-02-01	14306.235433	23148.864188	62279.780631	99734.880252
2022-03-01	15786.382943	22685.407035	65808.906593	104280.696572
2022-04-01	14527.731666	23807.779863	60196.598276	98532.109805
2022-05-01	12617.925482	21850.678640	58929.607574	93398.211696
2022-06-01	12966.525286	21237.825841	52754.638330	86958.989456
2022-07-01	14544.404321	20504.534953	55079.053393	90127.992667
2022-08-01	14019.139884	20360.850612	52692.503810	87072.494307
2022-09-01	12612.904342	18557.800423	46898.712031	78069.416796
2022-10-01	13370.344245	19755.952511	56465.223732	89591.520489
2022-11-01	14340.706042	21774.857789	57969.496427	94085.060258
2022-12-01	11951.679430	22122.427855	53178.119816	87252.227101

4.2.0 - Momentum trading strategy for S&P500

```
# Importing necessary library
import yfinance as yf

# Define the ticker symbol for S&P 500
ticker = '^GSPC'

# Download S&P 500 index data using yfinance
# 'start' is set to '2021-12-02' and 'end' is set to '2022-12-02'
# 'interval' is set to '1d' for daily data
sp500 = yf.download(ticker, start='2021-12-02', end='2022-12-02', interval='1d')

sp500
```

```
[*********************100%%**********************]  1 of 1 completed
```

Date	Open	High	Low	Close	Adj Close	Volume
2021-12-02	4504.729980	4595.459961	4504.729980	4577.100098	4577.100098	5077180000
2021-12-03	4589.490234	4608.029785	4495.120117	4538.430176	4538.430176	5240070000
2021-12-06	4548.370117	4612.600098	4540.509766	4591.669922	4591.669922	4770800000
2021-12-07	4631.970215	4694.040039	4631.970215	4686.750000	4686.750000	4492400000
2021-12-08	4690.859863	4705.060059	4674.520020	4701.209961	4701.209961	4234600000
...	...	...	...	...	...	...
2022-11-25	4023.340088	4034.020020	4020.760010	4026.120117	4026.120117	1706460000
2022-11-28	4005.360107	4012.270020	3955.770020	3963.939941	3963.939941	3615430000
2022-11-29	3964.189941	3976.770020	3937.649902	3957.629883	3957.629883	3546040000
2022-11-30	3957.179932	4080.110107	3938.580078	4080.110107	4080.110107	6579360000
2022-12-01	4087.139893	4100.509766	4050.870117	4076.570068	4076.570068	4527130000

252 rows × 6 columns

```
# Calculate 8-day moving average and assign it to a new column '8-day'
sp500['8-day'] = sp500['Close'].rolling(8).mean().shift()

# Calculate 21-day moving average and assign it to a new column '21-day'
sp500['21-day'] = sp500['Close'].rolling(21).mean().shift()

# Drop rows with missing values (NaN) introduced by the rolling averages
sp500.dropna(inplace=True)
```

```
# Calculate the logarithm of the closing prices and create a new column 'logClose'
sp500['logClose'] = np.log(sp500['Close'])

# Calculate the log returns and create a new column 'return'
sp500['return'] = sp500['logClose'].diff()
```

```
# Create a new column 'invested' using np.where()
# If the 8-day moving average is greater than the 21-day moving average, set 'invested' to
sp500['invested'] = np.where(sp500['8-day'] > sp500['21-day'], 1, 0)

# Create a new column 'signal' representing buy (1) and sell (-1) signals
sp500['signal'] = sp500['invested'].diff()

# Print the count of buy (1) and sell (-1) signals
print(sp500['signal'].value_counts())
```

```
 0.0    220
-1.0      5
 1.0      5
Name: signal, dtype: int64
```

```
# Buying on the first day
# Setting row with NaN to 1 for signal
sp500['signal'].iloc[0] = 1.0
#sp500['signal'].fillna(0, inplace=True)  # Fill any remaining NaN values with 0 (no signal
```

```
<ipython-input-66-50337fcde948>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
  sp500['signal'].iloc[0] = 1.0
```

```
# Calculate log returns and create a new column 'return'
sp500['return'] = np.log(sp500['Close']).diff()

# Set the first return value to 0.0
sp500['return'].iloc[0] = 0.0
```

```
<ipython-input-67-4c33e94d6d8c>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
  sp500['return'].iloc[0] = 0.0
```

```
# Calculate system returns by multiplying 'invested' with 'return'
sp500['system_return'] = sp500['invested'] * sp500['return']

# Display the first few rows of the DataFrame
sp500.head()
```

Date	Open	High	Low	Close	Adj Close	Volume	
2022-01-03	4778.140137	4796.640137	4758.169922	4796.560059	4796.560059	3831020000	4748.3
2022-01-04	4804.509766	4818.620117	4774.270020	4793.540039	4793.540039	4683170000	4766.8
2022-01-05	4787.990234	4797.700195	4699.439941	4700.580078	4700.580078	4887960000	4778.9
2022-01-06	4693.390137	4725.009766	4671.259766	4696.049805	4696.049805	4295280000	4775.7
2022-01-07	4697.660156	4707.950195	4662.740234	4677.029785	4677.029785	4181510000	4763.8

```
# Set the initial investment
initial_investment = 100000

# Calculate cumulative returns
sp500['cumulative_return'] = (1 + sp500['system_return']).cumprod()

# Calculate the value of the $100,000 investment over time
sp500['investment_value'] = initial_investment * sp500['cumulative_return']

sp500['investment_value']
```

```
Date
2022-01-03    100000.000000
2022-01-04     99937.017975
2022-01-05     97979.924938
2022-01-06     97885.449388
2022-01-07     97488.187059
                   ...
2022-11-25     89090.841497
2022-11-28     87704.169562
2022-11-29     87564.445094
2022-11-30     90233.290601
2022-12-01     90154.967218
Name: investment_value, Length: 231, dtype: float64
```

```
sp500['cumulative_return']
```

```
Date
2022-01-03    1.000000
2022-01-04    0.999370
2022-01-05    0.979799
2022-01-06    0.978854
```

```
2022-01-07    0.974882
                 ...
2022-11-25    0.890908
2022-11-28    0.877042
2022-11-29    0.875644
2022-11-30    0.902333
2022-12-01    0.901550
Name: cumulative_return, Length: 231, dtype: float64
```

```
# Extracting the investment value on the first day of each month
monthly_MT_values = sp500['investment_value'].resample('MS').first()

# Display the monthly investment values
print(monthly_MT_values)
```

```
Date
2022-01-01    100000.000000
2022-02-01     97098.407948
2022-03-01     91985.724470
2022-04-01     93684.596024
2022-05-01     91603.311289
2022-06-01     91603.311289
2022-07-01     81777.103571
2022-08-01     86255.628047
2022-09-01     84276.770236
2022-10-01     84276.770236
2022-11-01     85537.838023
2022-12-01     90154.967218
Freq: MS, Name: investment_value, dtype: float64
```

4.3 - Buy-and-Hold strategy for the S&P 500 index

```
import yfinance as yf

# Download S&P 500 index data using yfinance
ticker = '^GSPC'
start_date = '2022-01-01'
end_date = '2022-12-02'

# Use the 'download' method
sp500 = yf.download(ticker, start=start_date, end=end_date, interval='1mo')

# Select only the 'close' column and rename it
sp500 = sp500[['Close']]
sp500.columns = ['sp500_close']

# Display the first few rows of the DataFrame
sp500.head()
```

```
[*********************100%%**********************]  1 of 1 completed
```

	sp500_close
Date	
2022-01-01	4515.549805
2022-02-01	4373.939941
2022-03-01	4530.410156
2022-04-01	4131.930176
2022-05-01	4132.149902

```
# Calculate the logarithm of the S&P 500 closing prices and create a new column 'sp500_logC
sp500['sp500_logClose'] = np.log(sp500['sp500_close'])

# Calculate the log returns and create a new column 'sp500_return'
sp500['sp500_return'] = sp500['sp500_logClose'].diff()

# Display the first few rows of the DataFrame
sp500.head()
```

```
<ipython-input-73-c398f6e12a08>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
  sp500['sp500_logClose'] = np.log(sp500['sp500_close'])
<ipython-input-73-c398f6e12a08>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
  sp500['sp500_return'] = sp500['sp500_logClose'].diff()
```

	sp500_close	sp500_logClose	sp500_return
Date			

```
# Reset the first value of 'sp500_return' in the 'sp500' DataFrame to 0.0
sp500['sp500_return'].iloc[0]=0.0
# Create a new DataFrame 'sp500_returns' from the 'sp500_return' column of 'sp500'
sp500returns = pd.DataFrame(sp500["sp500_return"])
```

```
<ipython-input-74-52b7d0efee62>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
```