2024 MFIN 602 Team Project

Here is list of tasks: Construct a portfolio of stocks in the Energy sector/industry and government bonds. Collect financial data of the companies in the Energy sector/industry. See the list of names on the references Excel sheet. Use Refinitiv or Bloomberg to collect data.

PART A.

Choose 5-to-10 stocks for your portfolio according to their “Valuation” and “Price Momentum”.

1. Explain what measures of “Valuation” and “Momentum” do you use and why.
2. Which stocks do you choose? Explain the reasoning and method.
3. What are the weights of stocks? How do you decide?

In [92]:
```
import pandas as pd
import numpy as np
from scipy.optimize import minimize
import itertools
file_path = 'data/temp_602_data.xlsx'
df_header = pd.read_excel(file_path,header=0)
df = pd.read_excel(file_path,header=1)
df.head()
```

Out[92]:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_R
0	2023-10-31	54.4262	13.1222	12.20	11.3908	16
1	2023-11-01	61.6514	13.6700	12.34	11.5694	17
2	2023-11-02	67.4024	14.2077	12.64	11.7540	17
3	2023-11-03	66.3652	14.6169	12.95	11.7361	17
4	2023-11-06	64.5814	15.1469	12.92	11.7064	17

5 rows × 161 columns

Preprocessing Data

After parsing data from Bloomberg, we gain one Excel file. We first need to preprocess the data to make it easier to work with.

1. Drop columns with all missing values, such as NaN or unrealistic values from the excel file. (Done in Excel)

2. Create data frames for each stock for easier manipulation.

In [93]:
```
# Create a dictionary to store all DataFrame
dfs = {}
# Get stock names
stock_names = df_header.columns[1::5].str.replace(" ", "_")
#check stock_names
print(stock_names)
```

```
Index(['AM_US_Equity', 'AROC_US_Equity', 'BOOM_US_Equity', 'CEIX_US_Equity',
       'CHX_US_Equity', 'CIVI_US_Equity', 'CLB_US_Equity', 'CNX_US_Equity',
       'CPE_US_Equity', 'DTM_US_Equity', 'ETRN_US_Equity', 'HLX_US_Equity',
       'HP_US_Equity', 'LPG_US_Equity', 'MTDR_US_Equity', 'MUR_US_Equity',
       'NOV_US_Equity', 'OII_US_Equity', 'OIS_US_Equity', 'PARR_US_Equity',
       'PBF_US_Equity', 'PTEN_US_Equity', 'PUMP_US_Equity', 'RES_US_Equity',
       'REX_US_Equity', 'RRC_US_Equity', 'SLCA_US_Equity', 'SM_US_Equity',
       'SWN_US_Equity', 'TALO_US_Equity', 'TRGP_US_Equity', 'VTOL_US_Equity'],
      dtype='object')
```

In [94]:
```
# Go through the stock name and create their own DataFrame
for i, stock_name in enumerate(stock_names):
    cols = ['Dates'] + list(df.columns[i*5 + 1:i*5 + 6])
    stock_df = df[cols].copy()
    stock_df.columns = ['Dates', 'RSI_14D', 'REL_SHR_PX_MOMENTUM', 'PX_CLOSE_1D', 'CURRE
    # save the DataFrame to the dictionary
    dfs[f"{stock_name}_df"] = stock_df

# Check DataFrames
# for name, stock_df in dfs.items():
#     print(f"DataFrame for {name}:")
#     display(stock_df.head())
```

Explain what measures of “Valuation” and “Momentum” do you use and why.

We will use the following indicators to evaluate the valuation and momentum of each stock:

1. **Valuation**:
   - **Price-to-Earnings (P/E) Ratio**: The P/E ratio is a measure of a company's valuation. It indicates how much investors are willing to pay for each dollar of earnings. A lower P/E ratio may indicate that a stock is undervalued.
   - **EV/EBITDA Ratio**: The EV/EBITDA ratio is another valuation metric that compares a company's enterprise value to its earnings before interest, taxes, depreciation, and amortization. A lower EV/EBITDA ratio may indicate that a stock is undervalued.
2. **Momentum**:
   - **Relative Share Price Momentum**: The relative share price momentum measures the price momentum of a stock relative to the overall market. A positive relative share price momentum indicates that a stock is outperforming the market.
   - **RSI (Relative Strength Index)**: The RSI is a momentum oscillator that measures the speed and change of price movements. It ranges from 0 to 100 and is typically used to identify overbought or oversold conditions in a stock.

Which stocks do you choose? Explain the reasoning and method.

We will choose the top 5 stocks based on the average ranking of the following indicators:

1. **RSI_14D**: The average 14-day RSI value.
2. **REL_SHR_PX_MOMENTUM**: The average relative share price momentum.
3. **CURRENT_EV_TO_T12M_EBITDA**: The average current enterprise value to trailing twelve months EBITDA ratio.
4. **PE_RATIO**: The average price-to-earnings ratio.
5. **TOTAL_RANK**: The sum of the rankings of the above four indicators.
6. **RETURNS**: The daily returns of each stock based on the closing price.
7. **Correlation Matrix**: The correlation matrix of the daily returns of each stock.

Method:

We will calculate the average value of each indicator for each stock and rank the stocks based on these averages. The lower the average rank, the higher the stock's position in the final selection. We pick the top 10 stocks based on the total rank and use volatility and Sharpe ratio optimization to select the best combination of stocks.

In [95]:
```
# Initialize an empty DataFrame to store the ranking information
rank_df = pd.DataFrame()

# Go through each stock DataFrame and calculate the average values of the indicators
for name, stock_df in dfs.items():
    stock_name = name.replace("_df", "")

    # Calculate the average values of the indicators
    rsi_avg = stock_df['RSI_14D'].mean()
    momentum_avg = stock_df['REL_SHR_PX_MOMENTUM'].mean()
    ev_to_ebitda_avg = stock_df['CURRENT_EV_TO_T12M_EBITDA'].mean()
    pe_ratio_avg = stock_df['PE_RATIO'].mean()

    # Create a  DataFrame of the rank list based on the indicators in "valuation" and "m
    rank_info = pd.DataFrame({
        "RSI_14D_AVG": [rsi_avg],
        "REL_SHR_PX_MOMENTUM_AVG": [momentum_avg],
        "CURRENT_EV_TO_T12M_EBITDA_AVG": [ev_to_ebitda_avg],
        "PE_RATIO_AVG": [pe_ratio_avg]
    }, index=[stock_name])

    # Use pd.concat adding rank information to rank_df
    rank_df = pd.concat([rank_df, rank_info])

# Calculate rank
rank_df["RSI_14D_RANK"] = rank_df["RSI_14D_AVG"].rank(ascending=True)
rank_df["REL_SHR_PX_MOMENTUM_RANK"] = rank_df["REL_SHR_PX_MOMENTUM_AVG"].rank(ascending=
rank_df["CURRENT_EV_TO_T12M_EBITDA_RANK"] = rank_df["CURRENT_EV_TO_T12M_EBITDA_AVG"].ran
rank_df["PE_RATIO_RANK"] = rank_df["PE_RATIO_AVG"].rank(ascending=True)

# Sum up ranks
rank_df["TOTAL_RANK"] = (
    rank_df["RSI_14D_RANK"]
```

```
    + rank_df["REL_SHR_PX_MOMENTUM_RANK"]
    + rank_df["CURRENT_EV_TO_T12M_EBITDA_RANK"]
    + rank_df["PE_RATIO_RANK"]
)

# Sort by TOTAL_RANK in ascending order
rank_df = rank_df.sort_values(by="TOTAL_RANK", ascending=True)

# Display the results
rank_df.reset_index(inplace=True)
rank_df.rename(columns={'index': 'Stock'}, inplace=True)
display(rank_df)
```

	Stock	RSI_14D_AVG	REL_SHR_PX_MOMENTUM_AVG	CURRENT_EV_TO_T12M_EBITDA_
0	PARR_US_Equity	44.085725	-12.483676	3.555
1	PBF_US_Equity	45.360784	-11.347326	3.440
2	MUR_US_Equity	45.321266	-11.170992	3.090
3	CEIX_US_Equity	50.828905	6.211615	3.187
4	LPG_US_Equity	50.620866	14.384045	5.648
5	SM_US_Equity	51.593378	4.869292	3.664
6	CIVI_US_Equity	45.664069	-15.477718	3.860
7	MTDR_US_Equity	48.753570	-6.402370	4.724
8	RES_US_Equity	46.109671	-18.035006	4.102
9	HP_US_Equity	47.518555	-12.799495	4.430
10	PUMP_US_Equity	46.796553	-9.908327	4.912
11	SLCA_US_Equity	55.113707	1.385665	4.433
12	CNX_US_Equity	55.749972	7.237958	3.452
13	REX_US_Equity	50.494538	5.438140	6.000
14	TALO_US_Equity	45.852968	-19.772621	3.372
15	NOV_US_Equity	47.521642	-9.933644	8.824
16	BOOM_US_Equity	44.656575	-25.827202	5.797
17	PTEN_US_Equity	44.292035	-21.444129	5.379
18	CPE_US_Equity	56.506477	-20.685181	4.683
19	ETRN_US_Equity	50.697798	13.376021	13.473
20	HLX_US_Equity	50.134509	2.842673	5.64
21	RRC_US_Equity	49.430967	-5.441597	7.459
22	SWN_US_Equity	51.671686	-2.963441	6.591
23	CHX_US_Equity	48.395489	-9.343353	8.509
24	AROC_US_Equity	56.477186	20.410870	10.443
25	TRGP_US_Equity	61.648032	16.633652	10.625
26	OII_US_Equity	50.795253	-0.938635	9.498
27	DTM_US_Equity	60.559537	7.189550	14.295
28	OIS_US_Equity	45.402087	-28.364634	6.809
29	AM_US_Equity	54.484153	1.272426	12.750
30	VTOL_US_Equity	52.093479	2.814441	8.719
31	CLB_US_Equity	48.621519	-16.273861	11.852

Calculate Returns for each stock

We will calculate the daily returns for each stock using the 'PX_CLOSE_1D' column.

In [96]:
```
for name, stock_df in dfs.items():
    stock_df['RETURNS'] = stock_df['PX_CLOSE_1D'].pct_change().fillna(0)

# Check RETURNS DataFrame
for name, stock_df in dfs.items():
    print(f"DataFrame for {name} with RETURNS:")
    display(stock_df.head())
```

```
DataFrame for AM_US_Equity_df with RETURNS:
```

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	54.4262	13.1222	12.20	11.3908	16.7
1	2023-11-01	61.6514	13.6700	12.34	11.5694	17.1
2	2023-11-02	67.4024	14.2077	12.64	11.7540	17.5
3	2023-11-03	66.3652	14.6169	12.95	11.7361	17.5
4	2023-11-06	64.5814	15.1469	12.92	11.7064	17.4

```
DataFrame for AROC_US_Equity_df with RETURNS:
```

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	50.1156	22.5592	12.58	9.2570	24.0
1	2023-11-01	60.3212	23.1530	12.67	9.4623	24.9
2	2023-11-02	68.4889	23.8276	13.18	9.6881	26.1
3	2023-11-03	73.2355	24.7095	13.78	9.8807	27.0
4	2023-11-06	66.2905	25.7792	14.26	9.7563	26.4

```
DataFrame for BOOM_US_Equity_df with RETURNS:
```

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	27.3440	2.9762	18.82	6.2825	9.5
1	2023-11-01	26.3480	2.3356	18.95	6.2538	9.4
2	2023-11-02	29.7907	1.9457	18.79	6.2892	9.5
3	2023-11-03	20.1875	0.7083	18.99	5.9503	8.6
4	2023-11-06	19.1332	0.0545	17.10	5.8966	8.4

DataFrame for CEIX_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	35.3042	66.4999	102.17	2.5532	4.7
1	2023-11-01	43.2485	66.0444	91.89	2.6809	4.9
2	2023-11-02	45.5889	65.3920	96.44	2.7225	5.0
3	2023-11-03	45.4525	65.2470	97.92	2.7196	5.0
4	2023-11-06	43.2507	63.9978	97.82	2.6753	4.9

DataFrame for CHX_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	33.6253	17.0894	30.47	9.1757	18.3
1	2023-11-01	31.5422	16.5913	30.80	9.0299	18.0
2	2023-11-02	39.5327	15.9891	30.28	9.3188	18.6
3	2023-11-03	39.4364	15.5259	31.31	9.3132	18.6
4	2023-11-06	34.3086	15.1319	31.29	8.9934	17.9

DataFrame for CIVI_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	44.9654	3.8821	74.64	4.8019	8.0
1	2023-11-01	42.7767	4.1273	75.43	4.7731	8.0
2	2023-11-02	51.5078	4.1883	74.74	4.8721	8.2
3	2023-11-03	50.9777	4.4617	77.11	4.8659	8.2
4	2023-11-06	42.3158	5.4882	76.96	4.7501	7.9

DataFrame for CLB_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	32.4273	0.8444	21.52	13.6390	21.8
1	2023-11-01	30.0610	0.6785	21.42	13.4296	21.3
2	2023-11-02	33.0847	0.4987	21.02	13.5603	21.6
3	2023-11-03	32.2364	0.1652	21.25	13.4922	21.4
4	2023-11-06	27.7050	0.2954	21.12	13.0889	20.7

DataFrame for CNX_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	43.2216	36.9535	21.29	1.7496	9.9
1	2023-11-01	45.0890	37.5242	21.72	1.7559	9.9
2	2023-11-02	50.6065	37.8211	21.85	1.7756	10.1
3	2023-11-03	51.7526	38.0073	22.26	1.7799	10.2
4	2023-11-06	42.6376	38.4092	22.35	1.7429	9.8

DataFrame for CPE_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	45.5691	4.6950	37.27	4.4308	3.9
1	2023-11-01	42.1867	5.2540	37.35	4.3799	3.9
2	2023-11-02	44.4474	5.7371	36.80	4.3986	3.9
3	2023-11-03	39.4621	5.9701	37.08	4.3425	3.8
4	2023-11-06	34.6753	7.8986	36.24	4.2783	3.7

DataFrame for DTM_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	50.9742	8.0412	53.36	13.3165	16.0
1	2023-11-01	59.9043	8.6658	53.97	13.5285	16.4
2	2023-11-02	69.1054	9.3775	55.34	13.8417	17.1
3	2023-11-03	62.4968	9.6612	57.42	13.7077	16.8
4	2023-11-06	58.5661	10.3201	56.53	13.6204	16.6

DataFrame for ETRN_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	40.8862	79.5948	8.78	11.7413	12.4
1	2023-11-01	40.8862	79.2082	8.87	11.7413	12.4
2	2023-11-02	48.4768	79.2117	8.87	11.8388	12.7
3	2023-11-03	51.1217	78.9456	9.10	11.8770	12.8
4	2023-11-06	44.5536	77.3080	9.19	11.7752	12.5

DataFrame for HLX_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	37.1107	34.5391	9.77	4.6120	26.7
1	2023-11-01	39.0626	34.8780	9.80	4.6401	26.9
2	2023-11-02	48.2119	35.1254	9.87	4.7891	28.0
3	2023-11-03	47.1810	34.9043	10.24	4.7690	27.8
4	2023-11-06	42.8403	35.9680	10.19	4.6804	27.2

DataFrame for HP_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	39.9816	11.7843	39.33	4.4307	9.9
1	2023-11-01	38.7283	12.6167	39.57	4.4002	9.8
2	2023-11-02	49.4404	13.4125	39.28	4.5918	10.3
3	2023-11-03	50.7647	13.6105	41.10	4.6192	10.4
4	2023-11-06	43.2162	15.4585	41.36	4.4497	9.9

DataFrame for LPG_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	62.2306	35.4461	30.37	5.6459	5.0
1	2023-11-01	72.1113	36.4958	31.97	5.9753	5.5
2	2023-11-02	80.1431	38.0800	34.77	6.4727	6.1
3	2023-11-03	75.9255	40.1967	38.79	6.3876	6.0
4	2023-11-06	73.8899	42.0556	38.07	6.3462	6.0

DataFrame for MTDR_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	51.5833	18.5449	60.21	5.3465	8.9
1	2023-11-01	49.0036	19.7091	61.69	5.2958	8.8
2	2023-11-02	56.0187	20.8380	60.91	5.4460	9.2
3	2023-11-03	53.4153	21.4586	63.22	5.3966	9.1
4	2023-11-06	46.8445	24.1020	62.46	5.2581	8.7

DataFrame for MUR_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	45.6728	17.2718	44.92	3.5493	9.1
1	2023-11-01	45.2612	18.1559	44.87	3.5457	9.1
2	2023-11-02	54.9535	18.8870	44.81	3.5957	9.4
3	2023-11-03	53.2731	19.1711	46.14	3.5826	9.3
4	2023-11-06	46.0377	20.8724	45.92	3.5203	9.1

DataFrame for NOV_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	48.5495	8.3799	19.79	10.2590	15.5
1	2023-11-01	45.6667	9.0846	19.96	10.1473	15.3
2	2023-11-02	54.2304	9.6899	19.69	10.4739	15.9
3	2023-11-03	52.6468	9.8450	20.48	10.4160	15.8
4	2023-11-06	48.5063	11.6253	20.34	10.2590	15.5

DataFrame for OII_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	35.8031	34.7981	22.56	9.5083	37.6
1	2023-11-01	37.0346	34.4597	21.99	9.5616	37.9
2	2023-11-02	43.4241	33.9733	22.14	9.8531	39.3
3	2023-11-03	42.4621	33.6009	22.96	9.7926	39.0
4	2023-11-06	39.6259	33.8342	22.79	9.6113	38.1

DataFrame for OIS_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	39.5403	-4.3314	7.67	7.0920	77.8
1	2023-11-01	42.8198	-3.8740	7.26	7.2028	79.3
2	2023-11-02	49.7403	-3.3774	7.40	7.4641	82.8
3	2023-11-03	49.5446	-3.4048	7.73	7.4562	82.7
4	2023-11-06	46.2159	-2.1098	7.72	7.3216	80.9

DataFrame for PARR_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	48.0990	28.4937	32.39	3.1210	3.2
1	2023-11-01	49.6347	30.1058	32.82	3.1345	3.2
2	2023-11-02	49.1131	31.6218	33.00	3.1300	3.2
3	2023-11-03	45.2701	31.4264	32.94	3.0962	3.2
4	2023-11-06	44.1136	33.8790	32.49	3.0858	3.2

DataFrame for PBF_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	46.9584	23.7490	46.06	1.3608	2.9
1	2023-11-01	49.8932	25.0468	47.53	1.3790	3.(
2	2023-11-02	46.7344	26.0289	48.20	1.3438	2.9
3	2023-11-03	41.3548	25.9489	47.44	1.3048	2.8
4	2023-11-06	39.0197	27.4056	45.99	1.2860	2.8

DataFrame for PTEN_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	35.5634	8.9047	12.72	7.0092	8.3
1	2023-11-01	33.9198	9.5444	12.70	6.9471	8.2
2	2023-11-02	39.1146	10.0585	12.56	7.0535	8.3
3	2023-11-03	39.7522	10.1502	12.80	7.0668	8.3
4	2023-11-06	35.2472	11.9176	12.83	6.9160	8.1

DataFrame for PUMP_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	52.5449	38.5814	10.44	3.4488	7.3
1	2023-11-01	52.5449	39.9736	10.48	3.4488	7.3
2	2023-11-02	43.8857	40.9458	10.48	3.2601	7.0
3	2023-11-03	46.5220	41.3429	10.12	3.2915	7.1
4	2023-11-06	38.6915	43.6630	10.22	3.1658	6.8

DataFrame for RES_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	41.3849	11.2972	8.39	4.0432	7.7
1	2023-11-01	38.2161	11.9743	8.32	3.9587	7.6
2	2023-11-02	40.9548	12.2601	8.16	4.0063	7.6
3	2023-11-03	39.8967	12.1194	8.25	3.9799	7.6
4	2023-11-06	34.1893	12.8492	8.20	3.8214	7.3

DataFrame for REX_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	51.0901	27.5806	37.72	5.4897	13.7
1	2023-11-01	47.8781	27.4359	38.01	5.3776	13.5
2	2023-11-02	50.8012	27.1146	37.52	5.4760	13.7
3	2023-11-03	52.5988	26.9451	37.95	5.5377	13.7
4	2023-11-06	51.4736	26.8416	38.22	5.5034	13.7

DataFrame for RRC_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	64.2805	25.8778	34.60	4.6877	12.0
1	2023-11-01	68.2433	27.4688	35.84	4.7813	12.3
2	2023-11-02	70.9393	28.6707	36.69	4.8539	12.5
3	2023-11-03	69.7794	29.7310	37.35	4.8407	12.5
4	2023-11-06	54.5661	31.2474	37.23	4.6316	11.9

DataFrame for SLCA_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	30.1484	1.2330	12.29	3.6698	5.9
1	2023-11-01	28.4759	0.9066	12.07	3.6460	5.8
2	2023-11-02	34.3584	0.3207	11.93	3.6818	5.9
3	2023-11-03	31.8093	-0.0439	12.14	3.6504	5.8
4	2023-11-06	28.3518	-0.7553	11.95	3.6010	5.7

DataFrame for SM_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	49.0333	36.7529	39.82	3.5998	7.2
1	2023-11-01	45.1177	37.8463	40.32	3.5461	7.1
2	2023-11-02	53.4453	38.9949	39.57	3.6579	7.3
3	2023-11-03	49.9893	39.4876	41.13	3.5531	7.2
4	2023-11-06	43.2375	41.7235	40.47	3.4491	7.0

DataFrame for SWN_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	60.9369	30.5783	7.06	2.5958	9.3
1	2023-11-01	61.8097	32.0992	7.13	2.6028	9.4
2	2023-11-02	67.0890	33.3991	7.16	2.6501	9.7
3	2023-11-03	71.1668	34.5640	7.36	2.6950	9.9
4	2023-11-06	52.3992	36.6572	7.55	2.5745	9.2

DataFrame for TALO_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	44.5258	8.1707	15.33	3.2871	18.9
1	2023-11-01	39.0238	8.8079	15.50	3.2273	18.4
2	2023-11-02	47.6553	9.3080	15.04	3.3014	19.1
3	2023-11-03	45.8172	9.3666	15.61	3.2819	18.9
4	2023-11-06	37.1711	11.6165	15.46	3.1726	17.8

DataFrame for TRGP_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	43.2394	8.7538	83.60	8.6212	20.2
1	2023-11-01	46.0134	9.1463	83.61	8.6524	20.4
2	2023-11-02	66.1428	9.8181	84.15	8.9876	21.8
3	2023-11-03	58.0093	10.2280	90.25	8.8650	21.3
4	2023-11-06	55.9903	11.4343	88.12	8.8316	21.2

DataFrame for VTOL_US_Equity_df with RETURNS:

	Dates	RSI_14D	REL_SHR_PX_MOMENTUM	PX_CLOSE_1D	CURRENT_EV_TO_T12M_EBITDA	PE_RA
0	2023-10-31	35.8832	16.9063	26.09	9.7094	77.0
1	2023-11-01	35.0637	16.7608	26.14	9.6913	77.0
2	2023-11-02	61.7304	16.9874	26.05	10.2188	77.0
3	2023-11-03	66.8476	17.4230	28.60	10.3983	77.0
4	2023-11-06	57.9415	18.0486	29.49	10.2067	77.0

In [97]:
```
# Create a new DataFrame to store the 'RETURNS' column for all stocks
returns_df = pd.DataFrame()
sample_stock = next(iter(dfs.values()))
returns_df['Dates'] = sample_stock['Dates'].values

# Add each stock's 'RETURNS' column to returns_df
for name, stock_df in dfs.items():
    stock_name = name.replace("_df", "")  # Remove the suffix to obtain the stock name
    returns_df[stock_name] = stock_df['RETURNS']
```

```
display(returns_df)
```

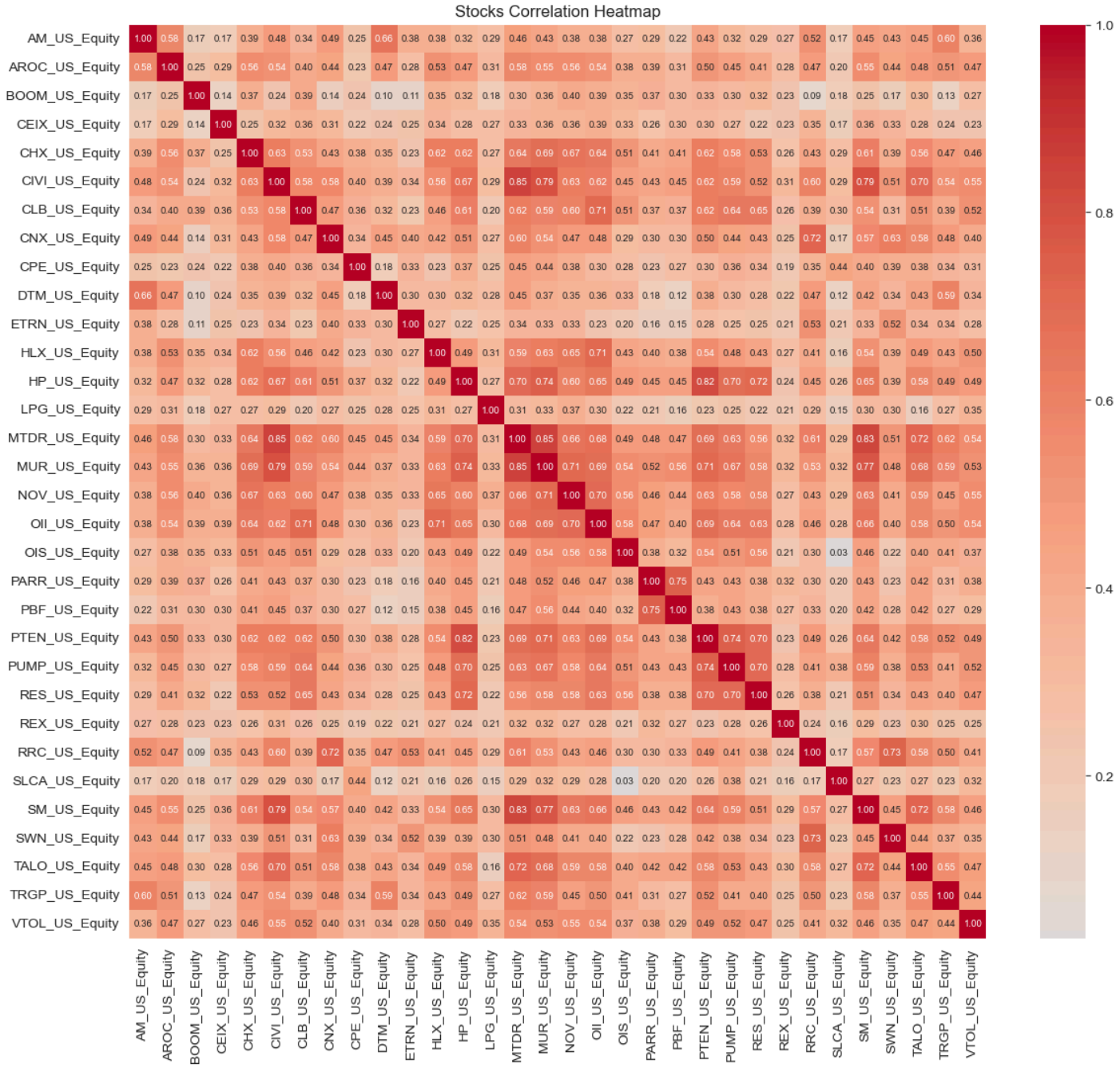
	Dates	AM_US_Equity	AROC_US_Equity	BOOM_US_Equity	CEIX_US_Equity	CHX_US_Equity	C
0	2023-10-31	0.000000	0.000000	0.000000	0.000000	0.000000	
1	2023-11-01	0.011475	0.007154	0.006908	-0.100617	0.010830	
2	2023-11-02	0.024311	0.040253	-0.008443	0.049516	-0.016883	
3	2023-11-03	0.024525	0.045524	0.010644	0.015346	0.034016	
4	2023-11-06	-0.002317	0.034833	-0.099526	-0.001021	-0.000639	
...	...	...	...	...	...	...	
259	2024-10-28	0.000667	0.012929	0.041206	0.011924	0.009990	
260	2024-10-29	-0.008661	0.005400	-0.010618	0.014567	-0.008186	
261	2024-10-30	0.000000	-0.008789	-0.020488	0.009419	-0.022696	
262	2024-10-31	0.008065	-0.007389	0.006972	-0.006523	-0.006334	
263	2024-11-01	-0.042000	-0.006452	-0.001978	0.011490	-0.000708	

264 rows × 33 columns

In [98]:
```
# Calculate the covariance matrix and correlation matrix
numeric_returns_df = returns_df.drop(columns=['Dates'])
cov_matrix = numeric_returns_df.cov()
# print("Covariance Matrix:")
# print(cov_matrix)

corr_matrix = numeric_returns_df.corr()
# print("Correlation Matrix:")
# print(corr_matrix)
```

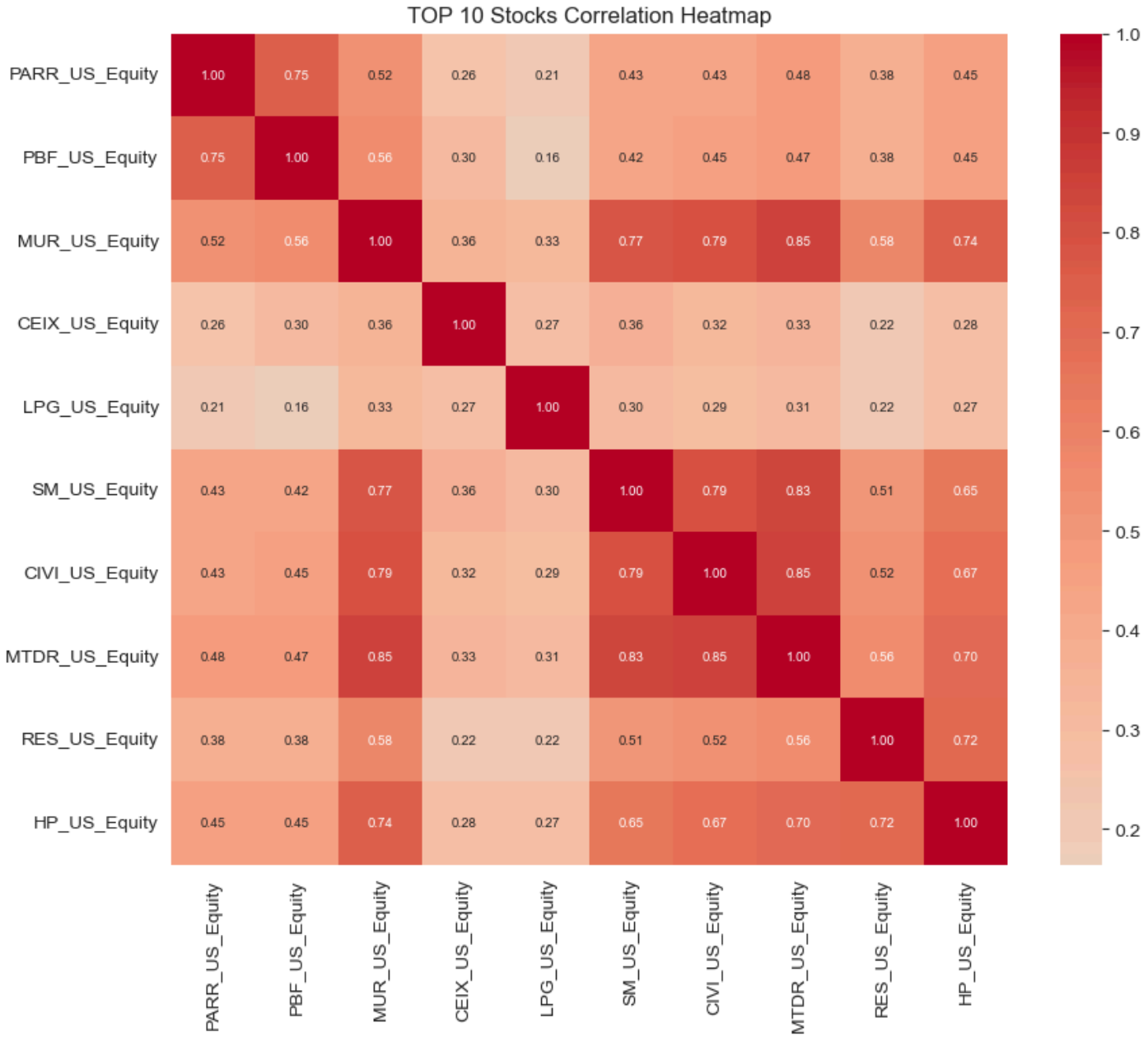
In [99]:
```
import seaborn as sns
import matplotlib.pyplot as plt
# visualize using heatmap
plt.figure(figsize=(14, 12))
sns.heatmap(
    corr_matrix,
    annot=True,
    cmap='coolwarm',
    center=0,
    fmt=".2f",
    annot_kws={"size": 7}
)
```

```
plt.title("Stocks Correlation Heatmap")
plt.show()
```



In [100…

```
# Calculate top 10 stocks correlation
top_10_stocks = rank_df['Stock'][0:10]
top_10_corr = corr_matrix.loc[top_10_stocks, top_10_stocks]
# Display top 10 stocks correlation with one hot encoding
plt.figure(figsize=(10, 8))
sns.heatmap(
    top_10_corr,
    annot=True,
    cmap='coolwarm',
    center=0,
    fmt=".2f",
    annot_kws={"size": 7}
)
plt.title("TOP 10 Stocks Correlation Heatmap")
plt.show()
```



In [101…

```
top_10_stocks = rank_df['Stock'][0:10]
top_10_corr = corr_matrix.loc[top_10_stocks, top_10_stocks]

# Retrieve the returns data for these stocks from returns_df
top_10_returns = returns_df[['Dates'] + list(top_10_stocks)]
display(top_10_returns)
# Calculate the average returns and covariance matrix for the top 10 stocks
expected_returns = top_10_returns.mean()  # The expected return for each stock
cov_matrix = top_10_returns.cov()         # The covariance matrix for the top 10 stocks
```

	Dates	PARR_US_Equity	PBF_US_Equity	MUR_US_Equity	CEIX_US_Equity	LPG_US_Equity	SM
0	2023-10-31	0.000000	0.000000	0.000000	0.000000	0.000000	
1	2023-11-01	0.013276	0.031915	-0.001113	-0.100617	0.052684	
2	2023-11-02	0.005484	0.014096	-0.001337	0.049516	0.087582	
3	2023-11-03	-0.001818	-0.015768	0.029681	0.015346	0.115617	
4	2023-11-06	-0.013661	-0.030565	-0.004768	-0.001021	-0.018561	
...	...	...	...	...	...	...	
259	2024-10-28	0.000000	0.010361	0.011416	0.011924	0.021732	
260	2024-10-29	0.016043	-0.018024	-0.028066	0.014567	-0.009024	
261	2024-10-30	-0.076023	-0.079747	-0.019774	0.009419	-0.013008	
262	2024-10-31	-0.007595	-0.008597	0.007045	-0.006523	-0.025371	
263	2024-11-01	-0.014668	-0.010753	0.000954	0.011490	-0.024679	

264 rows × 11 columns

Visualize functions

In [102…

```
import matplotlib.dates as mdates
from matplotlib.dates import DateFormatter
# Visualize the portfolio's return within 1 year.
def plot_returns_over_time(best_combination, top_returns_df):
    #pick the best combination return data.
    best_combination_returns = top_returns_df[['Dates'] + list(best_combination)].set_in

    plt.figure(figsize=(15, 6))

    for stock in best_combination_returns.columns:
        plt.plot(best_combination_returns.index, best_combination_returns[stock], label=

    plt.gca().xaxis.set_major_formatter(DateFormatter('%Y-%m'))
    plt.gca().xaxis.set_major_locator(mdates.MonthLocator())  # scale monthly

    plt.title("Returns Over Time for Selected Stocks in Best Combination")
    plt.xlabel("Time")
    plt.ylabel("Returns")
    plt.legend()
    plt.grid(True)

    plt.show()
```

In [103…

```
def plot_portfolio_returns_and_volatility(best_combination, top_returns_df, best_weights

    # Plot the daily return and volatility.
    best_combination_returns = top_returns_df[['Dates'] + list(best_combination)].set_in
    # Calculate the daily returns
    portfolio_daily_returns = best_combination_returns.dot(best_weights)
    # Calculate the rolling volatility
    rolling_volatility = portfolio_daily_returns.rolling(window=window).std()

    plt.figure(figsize=(15, 8))

    plt.subplot(2, 1, 1)
    plt.plot(portfolio_daily_returns.index, portfolio_daily_returns, label='Portfolio Da
    plt.title("Portfolio Daily Returns")
    plt.xlabel("Date")
    plt.ylabel("Returns")
    plt.legend()
    plt.grid(True)
    plt.gca().xaxis.set_major_formatter(DateFormatter('%Y-%m'))
    plt.gca().xaxis.set_major_locator(mdates.MonthLocator())


    plt.subplot(2, 1, 2)
    plt.plot(rolling_volatility.index, rolling_volatility, label=f'{window}-Day Rolling
    plt.title(f"Portfolio {window}-Day Rolling Volatility")
    plt.xlabel("Date")
    plt.ylabel("Volatility")
    plt.legend()
    plt.grid(True)
    plt.gca().xaxis.set_major_formatter(DateFormatter('%Y-%m'))
    plt.gca().xaxis.set_major_locator(mdates.MonthLocator())

    plt.tight_layout()
    plt.show()
```

Based on volatility, we calculate the optimal weights for the selected stock

In [104…

```
# Init
min_volatility = np.inf
best_combination = None
best_weights = None
best_corr_matrix = None

# Define the function of volatility.
def portfolio_volatility(weights, cov_matrix):
    return np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))

# The constraint is the weight should sum as 1
constraints = [
    {'type': 'eq', 'fun': lambda x: np.sum(x) - 1},  # Sum of weights = 1
    {'type': 'ineq', 'fun': lambda x: np.dot(x, expected_returns[list(combination)]) - 0
]

# The bound should be 0 to 1 for the weight.
bounds = tuple((0, 1) for _ in range(len(top_10_stocks)))
```

```
# Since we pick the top 10 stocks, we want to know if any combination is the best, we se
for r in range(5, 11):
    for combination in itertools.combinations(top_10_stocks, r):

        comb_returns = expected_returns[list(combination)]
        comb_cov_matrix = cov_matrix.loc[list(combination), list(combination)]
        comb_corr_matrix = comb_cov_matrix.corr()

        initial_weights = np.array([1 / r] * r)

        result = minimize(portfolio_volatility, initial_weights, args=(comb_cov_matrix,)
                          method='SLSQP', bounds=tuple((0.1, 0.5) for _ in range(r)), co

        # Check if the result is the best result.
        if result.success:
            comb_volatility = portfolio_volatility(result.x, comb_cov_matrix)

            if comb_volatility < min_volatility:
                min_volatility = comb_volatility
                best_combination = combination
                best_weights = result.x
                best_corr_matrix = comb_corr_matrix


print("Optimal Portfolio Allocation:")
for stock, weight in zip(best_combination, best_weights):
    print(f"{stock}: {weight:.2f}")
print("Minimum portfolio volatility:", min_volatility)

optimal_portfolio_return = np.dot(best_weights, expected_returns[list(best_combination)]
print("Optimal Portfolio Expected Return:", optimal_portfolio_return)

# print("\nCorrelation matrix for the best combination:")
# print(best_corr_matrix)
```

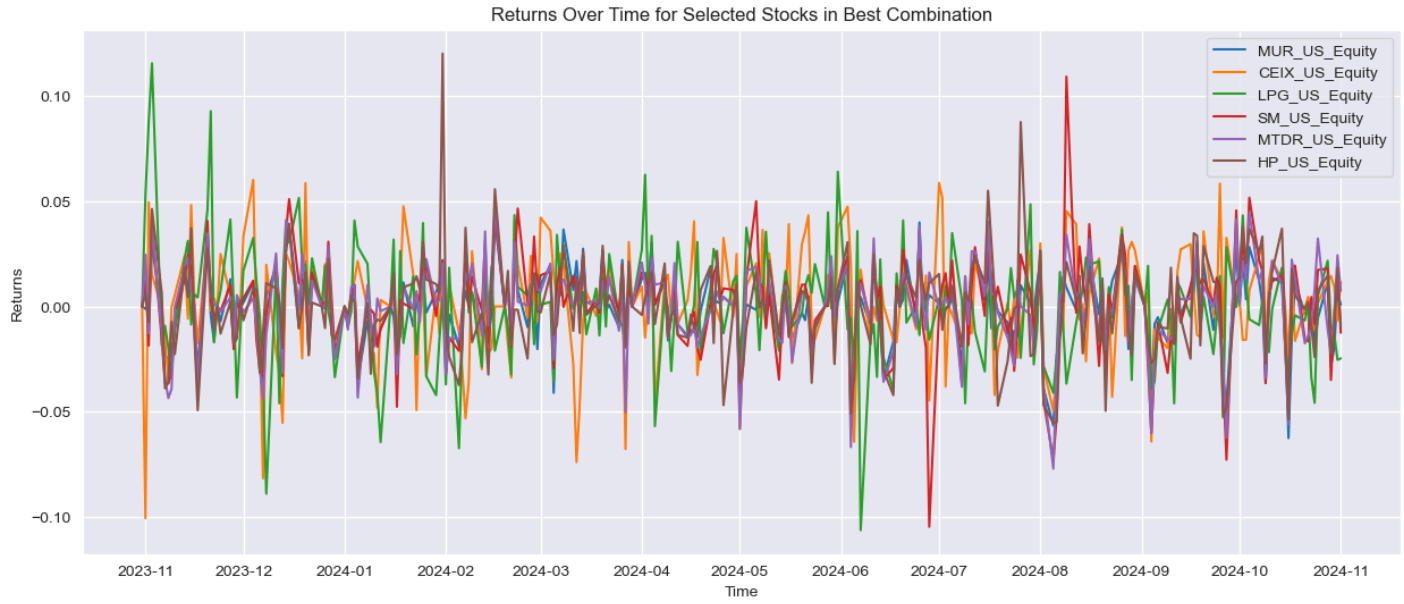
```
Optimal Portfolio Allocation:
MUR_US_Equity: 0.14
CEIX_US_Equity: 0.26
LPG_US_Equity: 0.22
SM_US_Equity: 0.12
MTDR_US_Equity: 0.13
HP_US_Equity: 0.12
Minimum portfolio volatility: 0.016643251902217274
Optimal Portfolio Expected Return: -2.0824989410868355e-14
```

In [ ]:

Visualize the results for volatility optimization

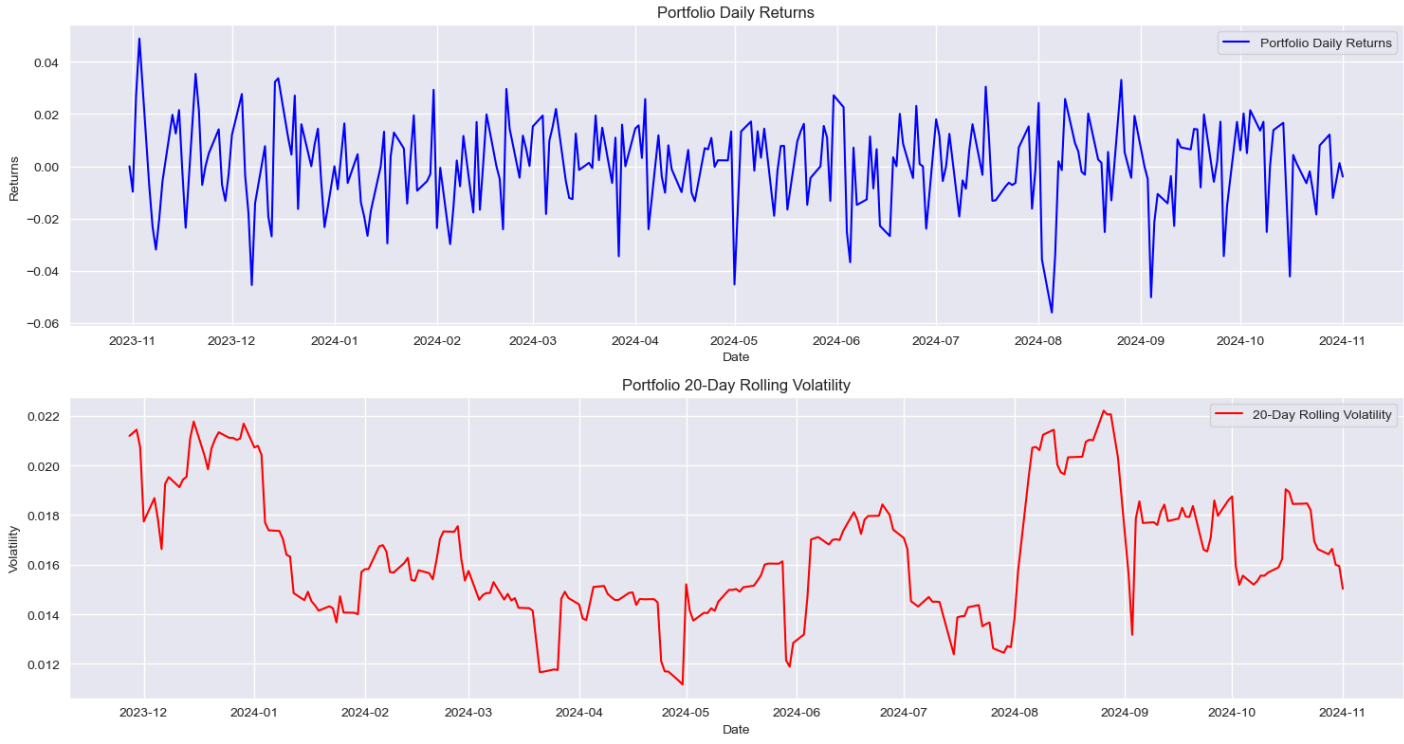
In [105…

```
plot_returns_over_time(best_combination, top_10_returns)
```



In [106…

```
plot_portfolio_returns_and_volatility(best_combination, top_10_returns, best_weights)
```



Based on Shape Ratio, we calculate the optimal weights for the selected stocks.

In [107…

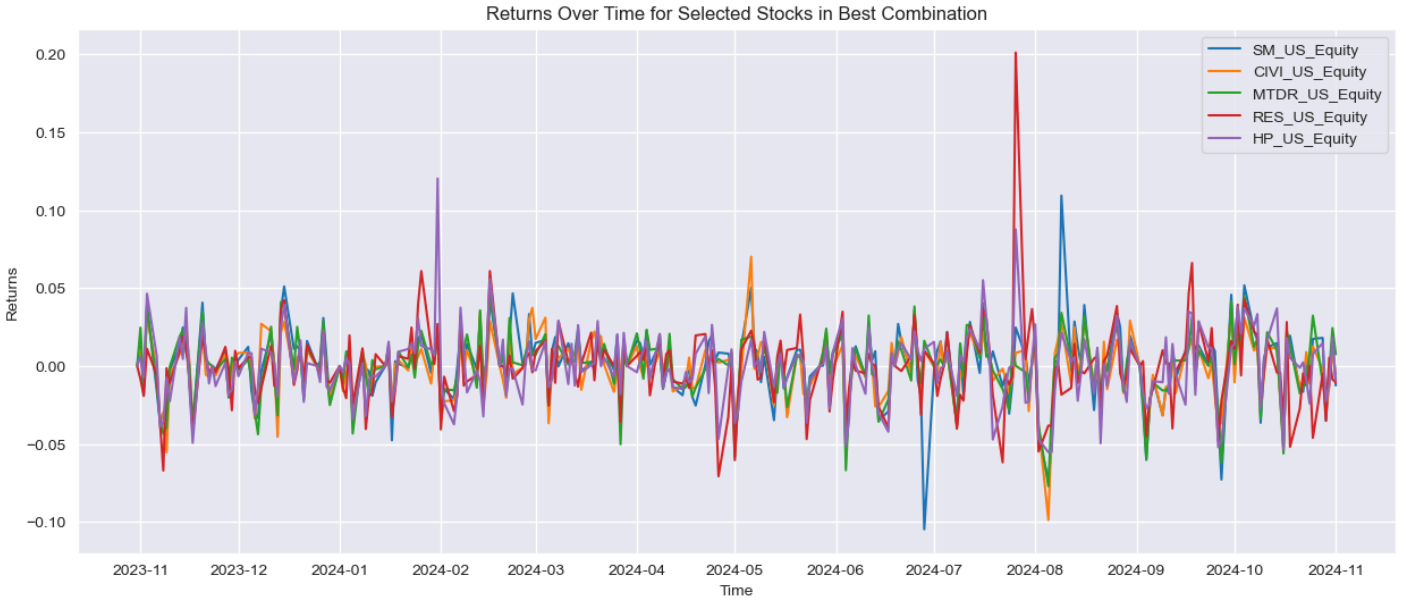
```
# We only need the data not the date column.
numeric_columns = top_10_returns.columns.difference(['Dates'])

# Calculate the top 10 expect return based on mean and cov matrix.
expected_returns = top_10_returns[numeric_columns].mean()
cov_matrix = top_10_returns[numeric_columns].cov()
# define the risk_free_rate here
risk_free_rate = 0.02

# define the negative sharpe_ratio, lower the better.
def neg_sharpe_ratio(weights, expected_returns, cov_matrix, risk_free_rate):
```

```
    portfolio_return = np.dot(weights, expected_returns)
    portfolio_volatility = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    sharpe_ratio = (portfolio_return - risk_free_rate) / portfolio_volatility
    return -sharpe_ratio

# Constrain the sum should be 1.
constraints = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1})

# Init data.
max_sharpe_ratio = -np.inf
best_combination = None
best_weights = None

# Go through all the combination and save the best result.
for r in range(5, 11):
    for combination in itertools.combinations(top_10_stocks, r):
        comb_returns = expected_returns[list(combination)]
        comb_cov_matrix = cov_matrix.loc[list(combination), list(combination)]

        initial_weights = np.array([1 / r] * r)

        # hyperparameter here, can adjust to truning the result.
        bounds = tuple((0.1, 0.5) for _ in range(r))

        # Optimize the weight based sharpe_ratio (since it's negative, we need find the
        result = minimize(
            neg_sharpe_ratio,
            initial_weights,
            args=(comb_returns, comb_cov_matrix, risk_free_rate),
            method='SLSQP',
            bounds=bounds,
            constraints=constraints
        )


        if result.success:
            sharpe_ratio = -result.fun
           #save the best result.
            if sharpe_ratio > max_sharpe_ratio:
                max_sharpe_ratio = sharpe_ratio
                best_combination = combination
                best_weights = np.round(result.x, 2)


optimal_portfolio_return = np.dot(best_weights, expected_returns[list(best_combination)]
optimal_portfolio_volatility = np.sqrt(np.dot(best_weights.T, np.dot(cov_matrix.loc[list


print("Optimal Portfolio Allocation:")
for stock, weight in zip(best_combination, best_weights):
    print(f"{stock}: {weight:.2f}")

print("Maximum Sharpe Ratio:", max_sharpe_ratio)
print("Optimal Portfolio Expected Return:", optimal_portfolio_return)
print("Optimal Portfolio Volatility:", optimal_portfolio_volatility)
```

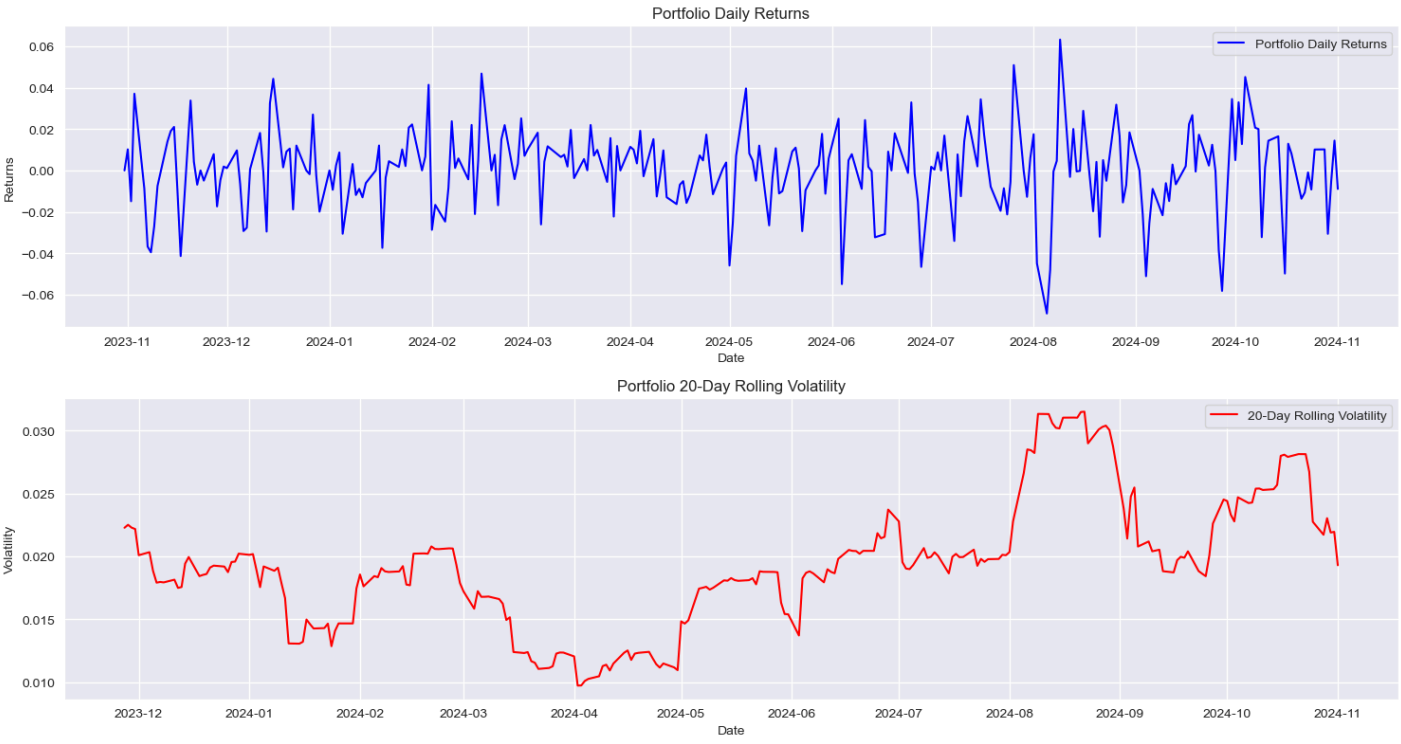
```
Optimal Portfolio Allocation:
SM_US_Equity: 0.50
CIVI_US_Equity: 0.10
MTDR_US_Equity: 0.10
RES_US_Equity: 0.10
HP_US_Equity: 0.20
Maximum Sharpe Ratio: -1.0129413387251405
Optimal Portfolio Expected Return: -0.0001309130329375487
Optimal Portfolio Volatility: 0.0198737204844199
```

Visualize the results for Sharpe Ratio optimization

In [108…
```
plot_returns_over_time(best_combination, top_10_returns)
```



In [109…
```
plot_portfolio_returns_and_volatility(best_combination, top_10_returns, best_weights)
```



In [ ]: