compiled_main

December 14, 2024

Install necessary packages

[1]:
```
pip install -r /workspaces/uzh-digfintools-research/requirements.txt
```

```
ERROR: Could not open requirements file: [Errno 2] No such file or
directory: '/workspaces/uzh-digfintools-research/requirements.txt'
Note: you may need to restart the kernel to use updated packages.
```

Equity data - D&J 60 from 2019-11-01 to 2020-11-01 (source: finance yahoo)

[2]:
```
import yfinance as yf
import pandas as pd
import os

tickers = ["MMM", "AXP", "AAPL", "BA", "CAT", "CVX", "CSCO", "KO", "DOW",
 ↪"XOM", "GS", "HD", "IBM", "INTC", "JNJ", "JPM", "MCD", "MRK", "MSFT", "NKE",
 ↪"PFE", "PG", "TRV", "UNH", "VZ", "V", "WBA", "WMT", "DIS", "RTX"]

start_date = '2019-11-01'
end_date = '2020-11-01'

data = yf.download(tickers, start=start_date, end=end_date,
 ↪interval='1d')['Close']

#Gather industry data
industry_data = []
for ticker in tickers:
  stock = (yf.Ticker(ticker)).info
  info = {
      'Ticker': ticker,
      'Industry': stock.get('industry', 'N/A'),
  }
  industry_data.append(info)
industry_df = pd.DataFrame(industry_data)
```

```
[*********************100%***********************]  30 of 30 completed
```

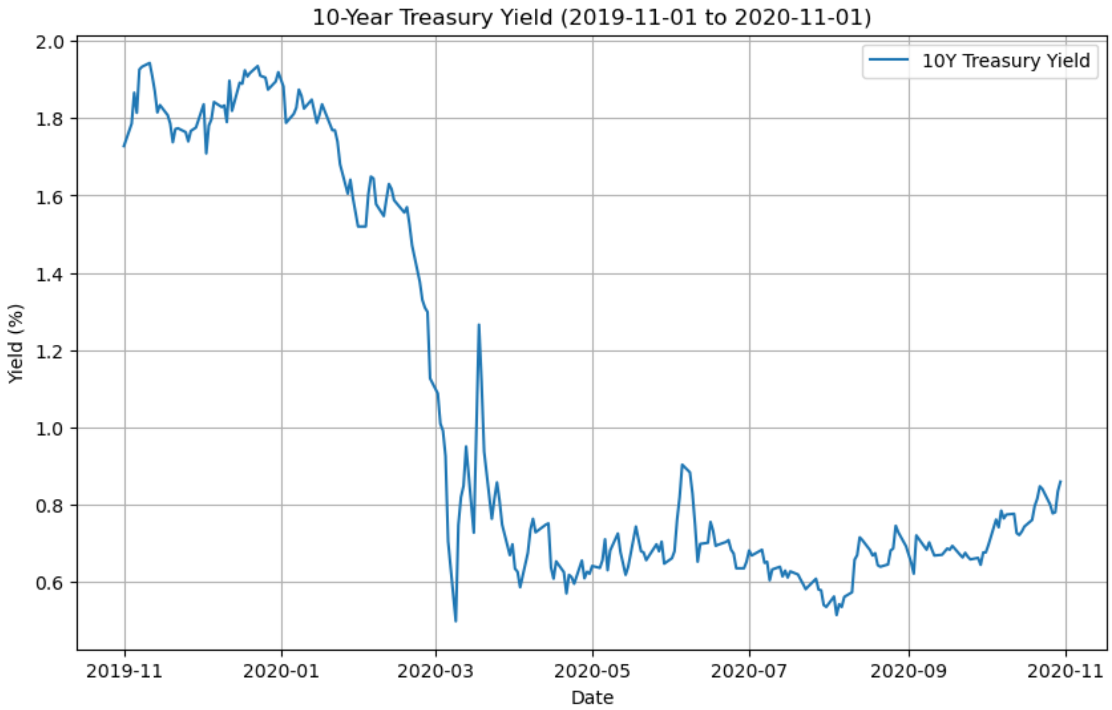
Risk-free data - T-bill 10Y yield for the same time period (source: finance yahoo)

[3]:
```python
import yfinance as yf
import pandas as pd
import os

ticker = "^TNX"

y10_data = yf.download(ticker, start=start_date, end=end_date,␣
↪interval='1d')['Close']
y10_data.head()
rf_rate = y10_data/100

descriptive_stats = rf_rate.describe()
descriptive_stats.head()
```

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

[3]:
```
Ticker        ^TNX
count   252.000000
mean      0.010363
std       0.005018
min       0.004990
25%       0.006627
```

[4]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
plt.plot(rf_rate*100, label='10Y Treasury Yield')
plt.title('10-Year Treasury Yield (2019-11-01 to 2020-11-01)')
plt.xlabel('Date')
plt.ylabel('Yield (%)')
plt.legend()
plt.grid(True)
plt.show()
```



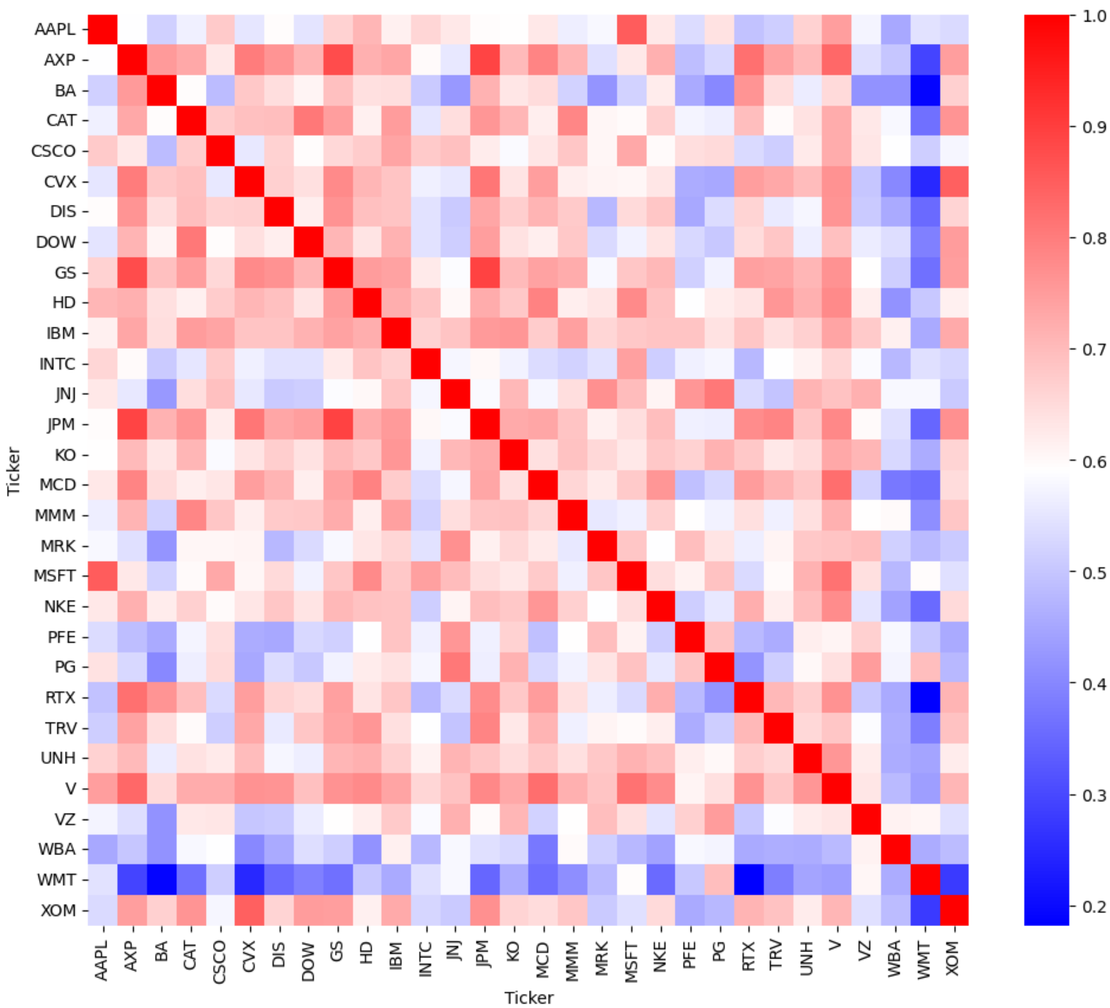
[5]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os

# Compute log returns
log_returns = np.log(data / data.shift(1)).dropna()

# Descriptive statistics (First 4 moments)
mean_returns = log_returns.mean()
variance = log_returns.var()
skewness = log_returns.skew()
kurtosis = log_returns.kurtosis()

# Combine the descriptive statistics into a DataFrame
descriptive_stats = pd.DataFrame({
    'Mean (%)': mean_returns*100,
    'Variance (%)': variance*100,
    'Skewness': skewness,
    'Kurtosis': kurtosis
})

# Associate with industries
descriptive_stats = descriptive_stats.merge(
```

```
    industry_df, how='left', left_on='Ticker', right_on='Ticker'
)

# Sort by Industry and Ticker for organization
descriptive_stats = descriptive_stats.sort_values(by=['Industry', 'Ticker'])

# Calculate the correlation matrix
correlation_matrix = log_returns.corr()

# Display descriptive statistics
#print("\nDescriptive Statistics (First 4 moments):\n", descriptive_stats)

#Export to Latex table
descriptive_latex = descriptive_stats.to_latex(index=False,na_rep='',␣
 ↪float_format="%.2f")
print(descriptive_latex)


correlation_matrix = log_returns.corr()

# Set up the matplotlib figure
plt.figure(figsize=(12, 10))

# Draw the heatmap
sns.heatmap(correlation_matrix, annot=False, cmap='bwr') #account for␣
 ↪colorblind color palette

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

```
\begin{tabular}{lrrrrl}
\toprule
Ticker &  Mean (\%) &  Variance (\%) &  Skewness &  Kurtosis &
Industry \\
\midrule
    BA &      -0.35 &           0.29 &     -0.32 &      6.21 &
Aerospace \& Defense \\
   RTX &      -0.21 &           0.12 &     -0.17 &      5.10 &
Aerospace \& Defense \\
   JPM &      -0.11 &           0.11 &     -0.21 &      6.74 &
Banks - Diversified \\
    KO &      -0.05 &           0.05 &     -0.77 &      4.14 &           Beverages
- Non-Alcoholic \\
    GS &      -0.06 &           0.10 &     -0.15 &      6.42 &
Capital Markets \\
   DOW &      -0.06 &           0.15 &     -1.13 &      9.67 &
Chemicals \\
```

```
  CSCO &     -0.11 &          0.07 &     -0.37 &      6.53 &
Communication Equipment \\
   MMM &     -0.02 &          0.06 &     -0.19 &      4.95 &
Conglomerates \\
  AAPL &      0.21 &          0.08 &     -0.34 &      4.41 &
Consumer Electronics \\
   AXP &     -0.11 &          0.14 &      0.40 &      7.39 &
Credit Services \\
     V &      0.00 &          0.07 &     -0.14 &      7.46 &
Credit Services \\
   WMT &      0.07 &          0.04 &      0.95 &      9.24 &
Discount Stores \\
   JNJ &      0.02 &          0.04 &      0.19 &      5.48 &        Drug
Manufacturers - General \\
   MRK &     -0.05 &          0.04 &     -0.11 &      4.33 &        Drug
Manufacturers - General \\
   PFE &     -0.03 &          0.04 &     -0.25 &      3.95 &        Drug
Manufacturers - General \\
   DIS &     -0.04 &          0.08 &     -0.09 &      5.78 &
Entertainment \\
   CAT &      0.03 &          0.08 &     -0.81 &      5.03 & Farm \& Heavy
Construction Machinery \\
   NKE &      0.12 &          0.07 &     -0.19 &      7.83 &
Footwear \& Accessories \\
   UNH &      0.08 &          0.09 &     -0.81 &      9.28 &
Healthcare Plans \\
    HD &      0.05 &          0.08 &     -1.93 &     18.19 &             Home
Improvement Retail \\
    PG &      0.04 &          0.04 &      0.12 &      8.23 &       Household \&
Personal Products \\
   IBM &     -0.08 &          0.07 &     -0.51 &      5.60 &     Information
Technology Services \\
   TRV &     -0.03 &          0.10 &     -2.17 &     16.60 &     Insurance -
Property \& Casualty \\
   CVX &     -0.20 &          0.14 &     -1.12 &     14.37 &                Oil
\& Gas Integrated \\
   XOM &     -0.30 &          0.10 &     -0.21 &      3.27 &                Oil
\& Gas Integrated \\
   WBA &     -0.21 &          0.08 &     -0.01 &      3.31 &
Pharmaceutical Retailers \\
   MCD &      0.04 &          0.06 &     -0.29 &     18.11 &
Restaurants \\
  INTC &     -0.10 &          0.11 &     -0.87 &     11.89 &
Semiconductors \\
  MSFT &      0.14 &          0.07 &     -0.46 &      7.64 &           Software
- Infrastructure \\
    VZ &     -0.02 &          0.02 &      0.50 &      5.75 &
Telecom Services \\
```

```
\bottomrule
\end{tabular}


/tmp/ipykernel_14/4199696470.py:38: FutureWarning: In future versions
`DataFrame.to_latex` is expected to utilise the base implementation of
`Styler.to_latex` for formatting and rendering. The arguments signature may
therefore change. It is recommended instead to use `DataFrame.style.to_latex`
which also contains additional functionality.
  descriptive_latex = descriptive_stats.to_latex(index=False,na_rep='',
float_format="%.2f")
```



[6]:
```
print(descriptive_stats.head())
```

```
   Ticker  Mean (%)  Variance (%)  Skewness  Kurtosis  \
2      BA -0.347242      0.290390 -0.324005  6.213240
22    RTX -0.211257      0.122471 -0.174238  5.097088
```

```
13    JPM -0.105614      0.106865 -0.205374   6.741553
14     KO -0.045689      0.045786 -0.773735   4.139190
8      GS -0.055671      0.104008 -0.154397   6.422341

                     Industry
2         Aerospace & Defense
22        Aerospace & Defense
13        Banks - Diversified
14   Beverages - Non-Alcoholic
8             Capital Markets
```

[7]:
```
#Define target portfolio return as average daily return of DJ in October 2019

import yfinance as yf
import pandas as pd
import os
import numpy as np

ticker = "^DJI"
dji_data = yf.download(ticker, start='2019-10-01', end='2019-10-31',␣
 ↪interval='1d')['Close']
dji_log_returns = np.log(dji_data / dji_data.shift(1)).dropna()
p0 = np.mean(dji_log_returns)
print(p0)
```

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

Ticker
^DJI    0.001087
dtype: float64


/opt/conda/lib/python3.10/site-packages/numpy/core/fromnumeric.py:3430:
FutureWarning: In a future version, DataFrame.mean(axis=None) will return a
scalar mean over the entire DataFrame. To retain the old behavior, use
'frame.mean(axis=0)' or just 'frame.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```

Markowtiz optimisation set up

[8]:
```
import numpy as np



fc = 21 #forecasting period: 21 - monthly
rb = 10 #rebalancing: 10 - biweekly
n = log_returns.shape[1] #number of securities
tdays = log_returns.shape[0]
tperiods = int(( tdays - fc) / rb) - 1 #number of forecasting periods
eqw = np.full(n, 1 / n)  # Equally weighted portfolio
```

```python
results_minvar = {
    'volatility_p': [],
    'return_p': [],
    'sharpe_ratio_p': [],
    'volatility_eqw': [],
    'return_eqw': [],
    'sharpe_ratio_eqw': [],
    'volatility_diff': [],
    'return_diff': [],
    'sharpe_ratio_diff': []
}


results_maxsr = {
    'volatility_p': [],
    'return_p': [],
    'sharpe_ratio_p': [],
    'volatility_eqw': [],
    'return_eqw': [],
    'sharpe_ratio_eqw': [],
    'volatility_diff': [],
    'return_diff': [],
    'sharpe_ratio_diff': []
}

riskfree_rate = rf_rate.values
```

Minimum variance optimisation

[9]:
```python
import cvxopt
import numpy as np

cvxopt.solvers.options['show_progress'] = False

for i in range(tperiods):
    # Extract the rolling window
    window = log_returns.iloc[i * rb: fc + i * rb, :]
    window_cov = window.cov()
    log_returns_target = np.mean(window, axis=0)


    # Initialize quadratic programming problem to minimise variance
    P = 2 * cvxopt.matrix(window_cov.values) # Covariance matrix (for variance␣
↪minimization)
    q = cvxopt.matrix(np.zeros(n)) # No linear term in minimisation problem
```

```
    # Constraints: no short selling (weights >= 0) and minimum portfolio return constraint
    G = cvxopt.matrix(np.vstack([-np.eye(n), log_returns_target]))
    h = cvxopt.matrix(np.append(np.zeros(n), -p0))

    # Fully invested portfolio: sum of weights = 1
    A = cvxopt.matrix(np.ones([1, n]))
    b = cvxopt.matrix([1.0])

    #Run optimisation problem
    sol = cvxopt.solvers.qp(P,q, G, h, A, b)

    #Check for optimisation failures
    if sol['status'] != 'optimal':
        print(f"Optimisation failed at iteration {i}")
        continue

    #Extract optimised weights
    weights = np.array(sol['x']).flatten()

    #Back-testing

    return_bt = log_returns.iloc[fc + (i + 1) * rb, :].values #Realised return
    variance_bt = log_returns.iloc[i * rb: fc + (i + 1) * rb, :].cov() #Realised covariance

    # Optimal portfolio variance, return and sharpe ratio calculatoin
    variance_p = weights.T @ variance_bt @ weights #Potrfolio variance (daily data)
    volatility_p = np.sqrt(variance_p) #Portfolio volatility (daily data)
    return_p = weights.T @ return_bt #Portfolio return daily
    sr_p = (return_p - riskfree_rate[i])/volatility_p #Portfolio Sharpe ratio

    #Calculate performance of benchmark - equally weighted portfolio
    volatility_bench = np.sqrt(eqw.T @ variance_bt @ eqw) #Benchmark variance (daily data)
    return_bench = eqw.T@return_bt #Benchmark daily returns
    sr_bench = (return_bench - riskfree_rate[i])/volatility_bench #Benchmark Sharpe ratio

    #Calculate differences in performance measures for optimised portfolio against benchmark
    volatility_diff = volatility_p-volatility_bench #Difference in volatility
    return_diff = return_p - return_bench #Difference in daily returns
    sr_diff = sr_p - sr_bench #Difference in Sharpe ratios
```

```python
    # Store results
    results_minvar['volatility_p'].append(volatility_p)
    results_minvar['return_p'].append(return_p)
    results_minvar['sharpe_ratio_p'].append(sr_p)
    results_minvar['volatility_eqw'].append(volatility_bench)
    results_minvar['return_eqw'].append(return_bench)
    results_minvar['sharpe_ratio_eqw'].append(sr_bench)
    results_minvar['volatility_diff'].append(volatility_diff)
    results_minvar['return_diff'].append(return_diff)
    results_minvar['sharpe_ratio_diff'].append(sr_diff)
```

Maximum Sharpe Ratio

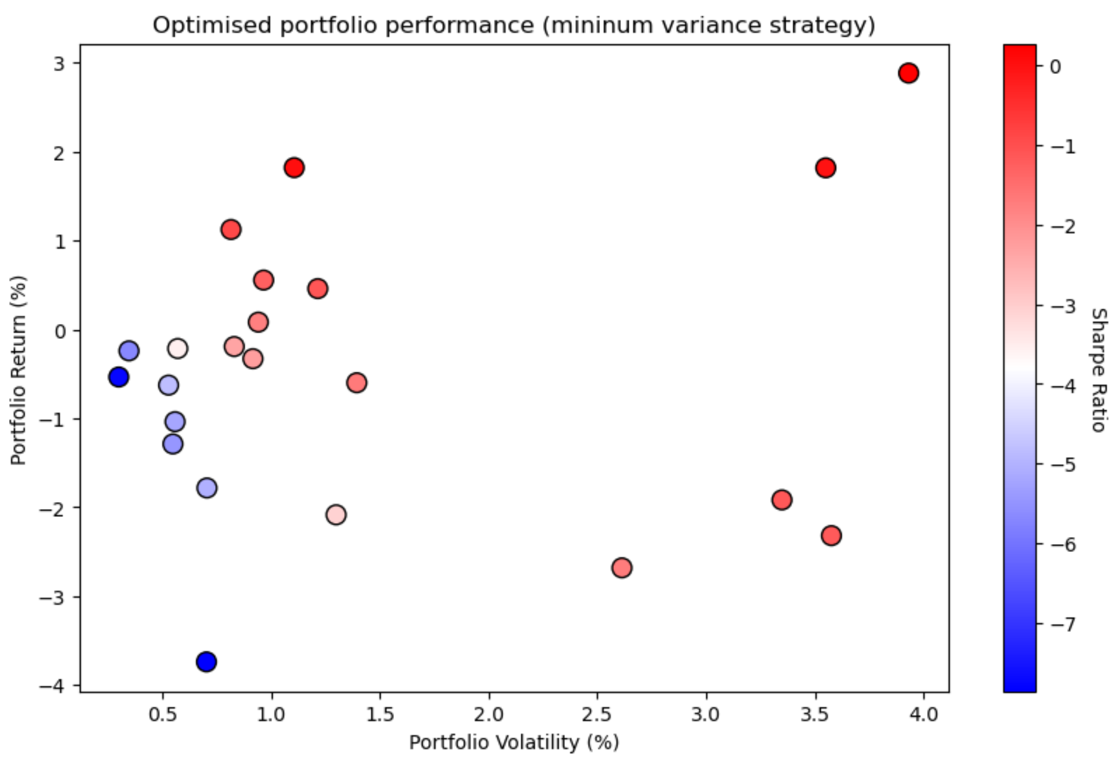
[10]:
```python
import cvxopt
import numpy as np

cvxopt.solvers.options['show_progress'] = False

for i in range(tperiods):
    # Extract the rolling window
    window = log_returns.iloc[i * rb: fc + i * rb, :]
    window_cov = window.cov()
    log_returns_target = np.mean(window, axis=0)

    # Calculate the excess returns (numerator in Sharpe ratio formula)
    excess_returns = log_returns_target - riskfree_rate[i]

    # Initialize quadratic programming problem to maximize Sharpe ratio
    P = cvxopt.matrix(window_cov.values)  # Covariance matrix (for variance␣
 ↪minimization)
    q = cvxopt.matrix(-excess_returns)     # Negative of the excess returns (we␣
 ↪want to maximize returns)

    # Constraints: no short selling (weights >= 0)
    G = cvxopt.matrix(np.vstack([-np.eye(n)]))
    h = cvxopt.matrix(np.zeros(n))

    # Fully invested portfolio: sum of weights = 1
    A = cvxopt.matrix(np.ones([1, n]))
    b = cvxopt.matrix([1.0])

    # Run optimization problem
    sol = cvxopt.solvers.qp(P, q, G, h, A, b)

    if sol['status'] != 'optimal':
        print(f"Optimization failed at iteration {i}")
```

```
        continue

    weights = np.array(sol['x']).flatten()  # Optimal weights

    #Back-testing

    return_bt = log_returns.iloc[fc + (i + 1) * rb, :].values #Realised return
    variance_bt = log_returns.iloc[i * rb: fc + (i + 1) * rb, :].cov()␣
↪#Realised covariance

    # Optimal portfolio variance, return and sharpe ratio calculatoin
    variance_p = weights.T @ variance_bt @ weights #Potrfolio variance (daily␣
↪data)
    volatility_p = np.sqrt(variance_p) #Portfolio volatility (daily data)
    return_p = weights.T @ return_bt #Portfolio return daily
    sr_p = (return_p - riskfree_rate[i])/volatility_p #Portfolio Sharpe ratio

    #Calculate performance of benchmark - equally weighted portfolio
    volatility_bench = np.sqrt(eqw.T @ variance_bt @ eqw) #Benchmark variance␣
↪(daily data)
    return_bench = eqw.T@return_bt #Benchmark daily returns
    sr_bench = (return_bench - riskfree_rate[i])/volatility_bench #Benchmark␣
↪Sharpe ratio

    #Calculate differences in performance measures for optimised portfolio␣
↪against benchmark
    volatility_diff = volatility_p-volatility_bench #Difference in volatility
    return_diff = return_p - return_bench #Difference in daily returns
    sr_diff = sr_p - sr_bench #Difference in Sharpe ratios

    # Store results
    results_maxsr['volatility_p'].append(volatility_p)
    results_maxsr['return_p'].append(return_p)
    results_maxsr['sharpe_ratio_p'].append(sr_p)
    results_maxsr['volatility_eqw'].append(volatility_bench)
    results_maxsr['return_eqw'].append(return_bench)
    results_maxsr['sharpe_ratio_eqw'].append(sr_bench)
    results_maxsr['volatility_diff'].append(volatility_diff)
    results_maxsr['return_diff'].append(return_diff)
    results_maxsr['sharpe_ratio_diff'].append(sr_diff)
```

Plots

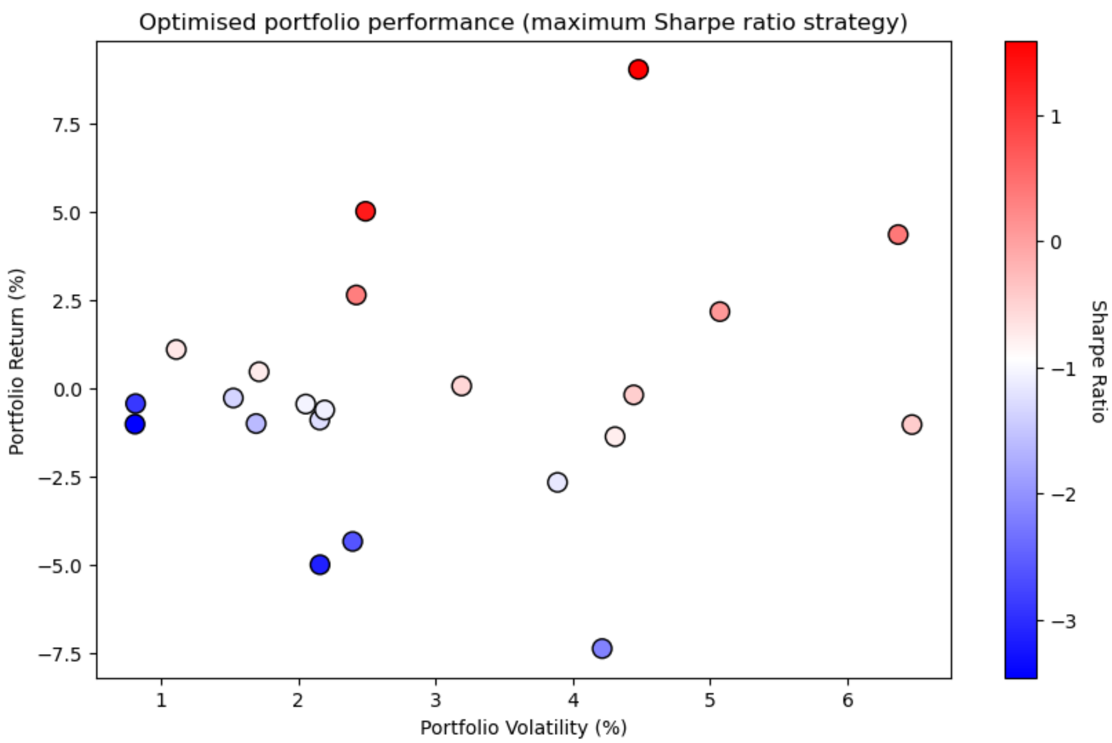
[11]:
```
# Scatter plot for Minimum Variance Strategy
plt.figure(figsize=(10, 6))

# Extracting data for the minimum variance strategy
```

```
returns_minvar = np.array(results_minvar['return_p'])*100  # Portfolio returns
volatility_minvar = np.array(results_minvar['volatility_p'])*100  # Portfolio␣
↪volatility
sharpe_ratios_minvar = np.array(results_minvar['sharpe_ratio_p'])  # Sharpe␣
↪ratios

# Scatter plot with Sharpe ratio as color
sc_minvar = plt.scatter(volatility_minvar, returns_minvar,␣
↪c=sharpe_ratios_minvar, cmap='bwr', s=100, edgecolor='k')
cbar_minvar = plt.colorbar(sc_minvar)
cbar_minvar.set_label('Sharpe Ratio', rotation=270, labelpad=15)

plt.xlabel('Portfolio Volatility (%)')
plt.ylabel('Portfolio Return (%)')
plt.title('Optimised portfolio performance (mininum variance strategy)')
plt.show()
```



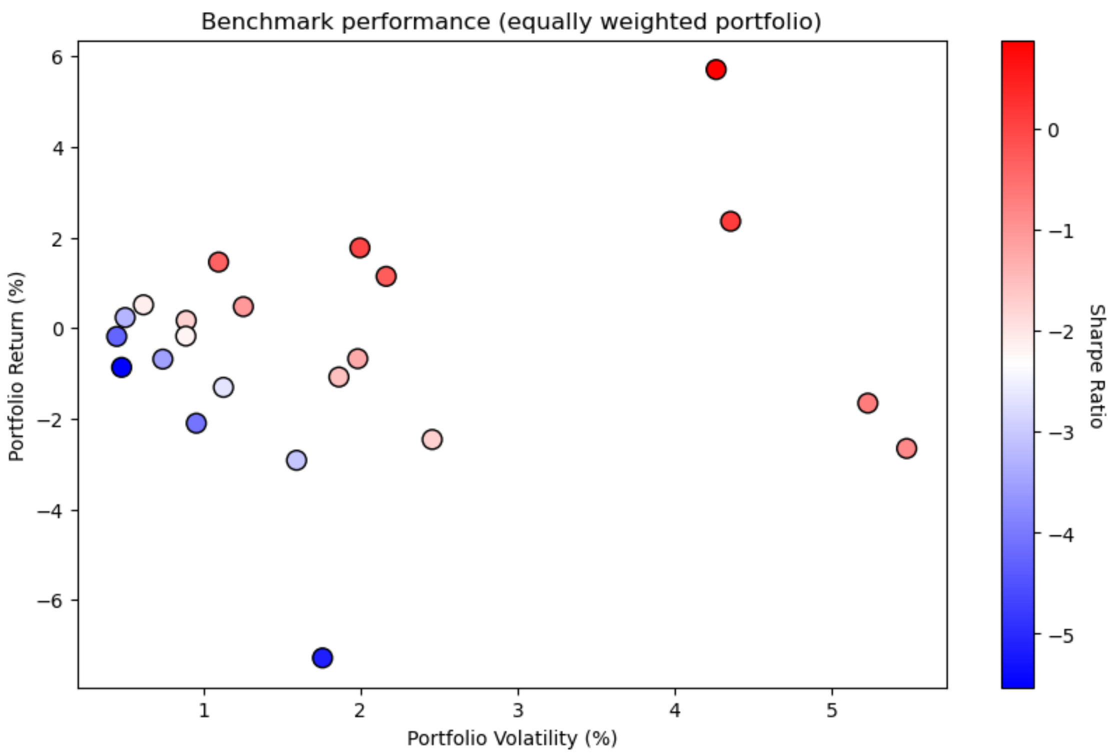
[12]:
```
# Scatter plot for Maximum Sharpe Ratio Strategy
plt.figure(figsize=(10, 6))

# Extracting data for the maximum Sharpe ratio strategy
returns_maxsr = np.array(results_maxsr['return_p'])*100  # Portfolio returns
```

```
volatility_maxsr = np.array(results_maxsr['volatility_p'])*100  # Portfolio␣
↪volatilities (already sqrt of variance)
sharpe_ratios_maxsr = np.array(results_maxsr['sharpe_ratio_p'])  # Sharpe ratios

# Scatter plot with Sharpe ratio as color
sc_maxsr = plt.scatter(volatility_maxsr, returns_maxsr, c=sharpe_ratios_maxsr,␣
↪cmap='bwr', s=100, edgecolor='k')
cbar_maxsr = plt.colorbar(sc_maxsr)
cbar_maxsr.set_label('Sharpe Ratio', rotation=270, labelpad=15)

plt.xlabel('Portfolio Volatility (%)')
plt.ylabel('Portfolio Return (%)')
plt.title('Optimised portfolio performance (maximum Sharpe ratio strategy)')
plt.show()
```



[13]:
```
# Scatter plot for benchmark portfolio
plt.figure(figsize=(10, 6))

# Extracting data for benchmark
returns_b = np.array(results_maxsr['return_eqw'])*100  # Portfolio returns
volatility_b = np.array(results_maxsr['volatility_eqw'])*100  # Portfolio␣
↪volatilities (already sqrt of variance)
sharpe_ratios_b = np.array(results_maxsr['sharpe_ratio_eqw'])  # Sharpe ratios
```

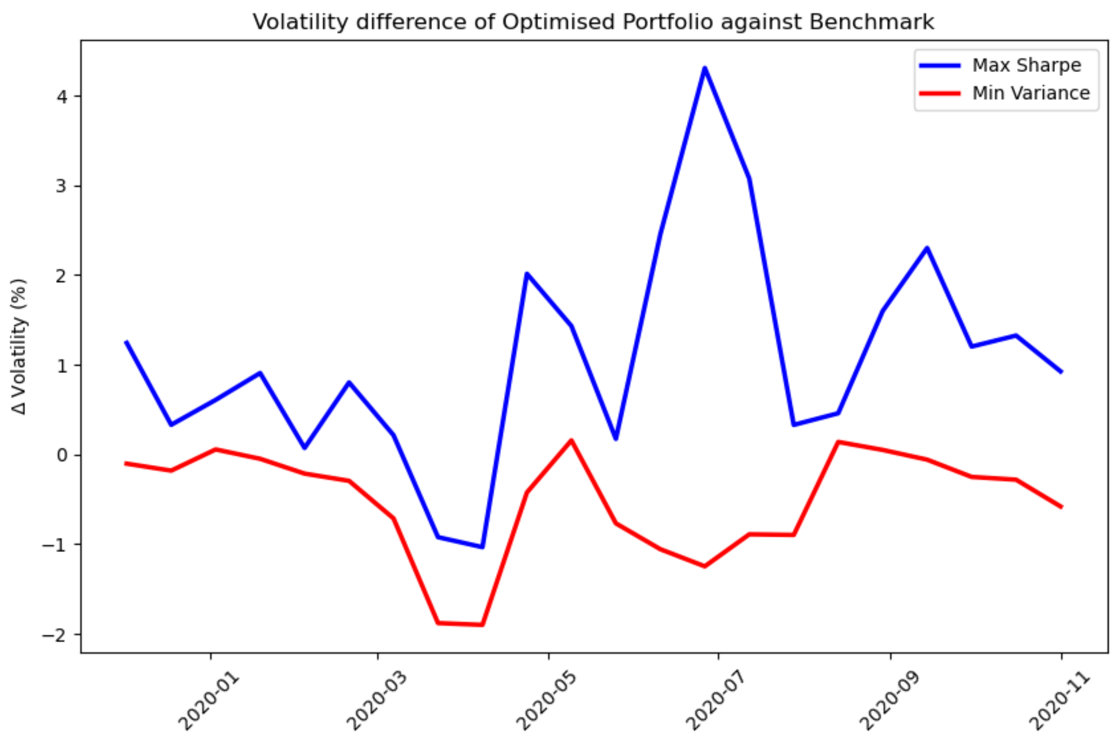
```
# Scatter plot with Sharpe ratio as color
sc_b = plt.scatter(volatility_b, returns_b, c=sharpe_ratios_b, cmap='bwr',␣
 ↪s=100, edgecolor='k')
cbar_b = plt.colorbar(sc_b)
cbar_b.set_label('Sharpe Ratio', rotation=270, labelpad=15)

plt.xlabel('Portfolio Volatility (%)')
plt.ylabel('Portfolio Return (%)')
plt.title('Benchmark performance (equally weighted portfolio)')
plt.show()
```

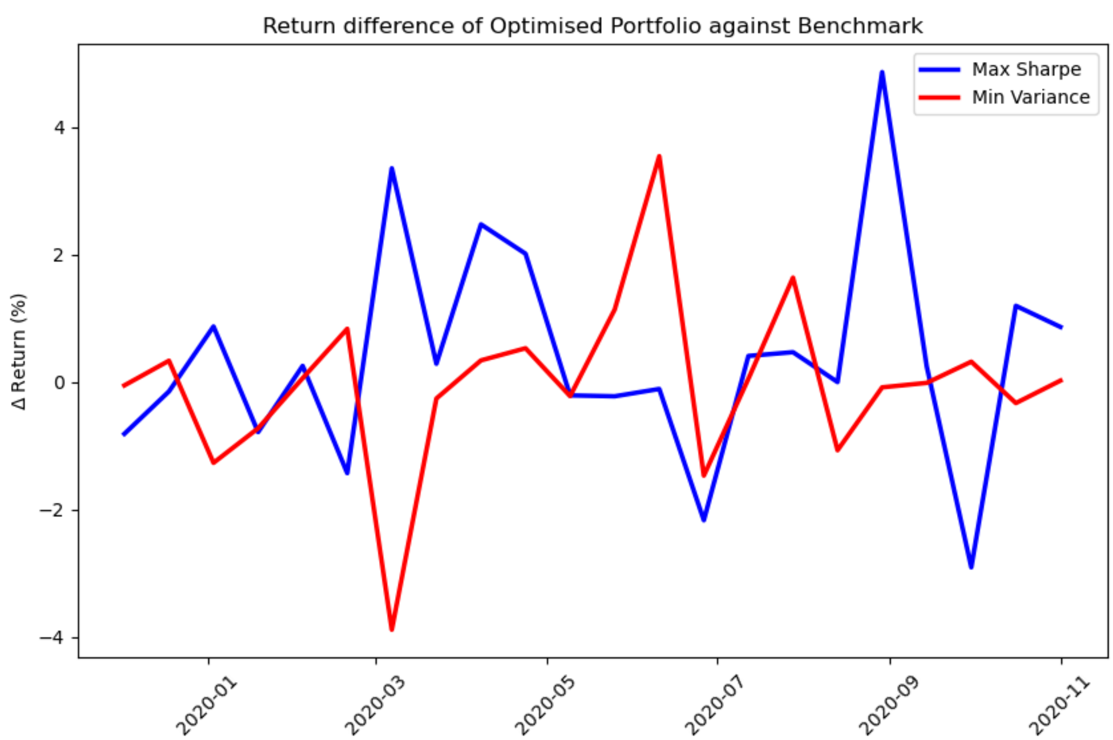


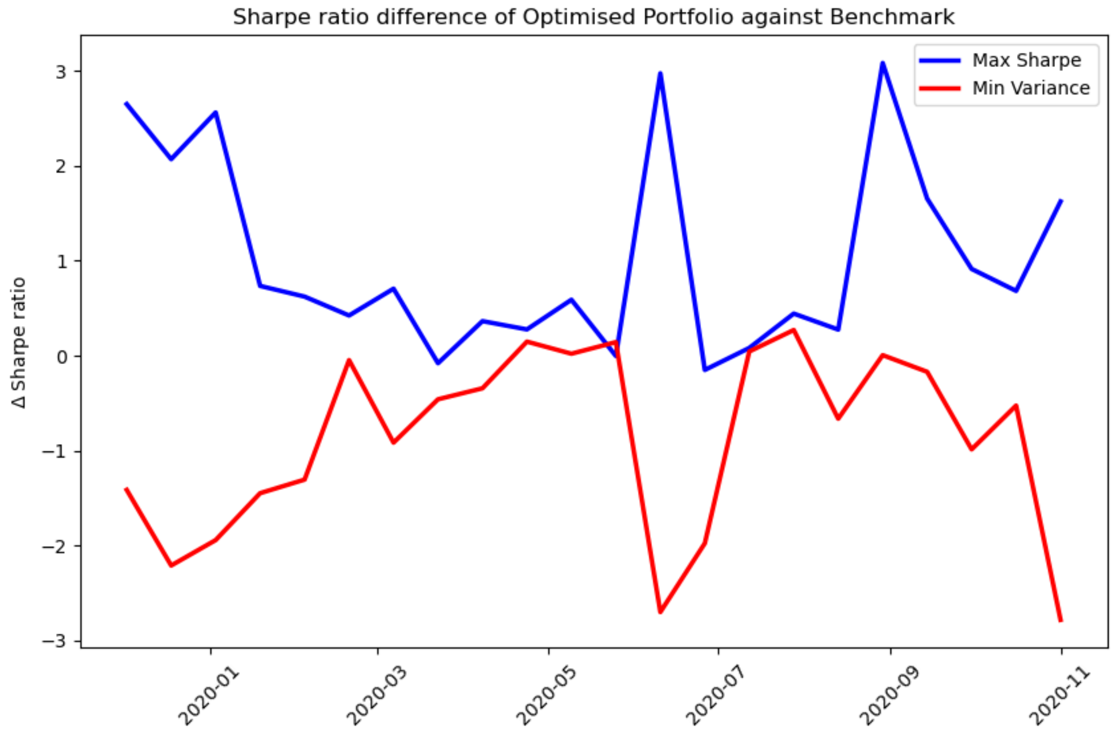
[14]:
```
#Generate dates

import pandas as pd
# The initial start date
start_date = pd.to_datetime("2019-11-01")
end_date = pd.to_datetime("2020-11-01")
start_f_date = start_date + pd.tseries.offsets.BDay(fc) #forecasting period␣
 ↪using as step
dates_df = pd.date_range(start=start_f_date, end=end_date, periods=tperiods)
len(dates_df)
```

[14]: 22

[15]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Plotting volatility for both portfolios
plt.figure(figsize=(10, 6))
plt.plot(dates_df, np.array(results_maxsr['volatility_diff'])*100, label="Max␣
↪Sharpe", color='blue', linewidth=2.5)
plt.plot(dates_df, np.array(results_minvar['volatility_diff'])*100, label="Min␣
↪Variance", color='red', linewidth=2.5)
plt.ylabel("$\Delta$ Volatility (%)")
plt.title("Volatility difference of Optimised Portfolio against Benchmark")
plt.xticks(rotation=45)
plt.legend()
plt.show()


# Plotting returns for both portfolios
plt.figure(figsize=(10, 6))
plt.plot(dates_df, np.array(results_maxsr['return_diff'])*100, label="Max␣
↪Sharpe", color='blue', linewidth=2.5)
plt.plot(dates_df, np.array(results_minvar['return_diff'])*100, label="Min␣
↪Variance", color='red', linewidth=2.5)
plt.ylabel("$\Delta$ Return (%)")
plt.title("Return difference of Optimised Portfolio against Benchmark")
plt.xticks(rotation=45)
plt.legend()
plt.show()

# Plotting Sharpe ratio difference for both portfolios
plt.figure(figsize=(10, 6))
plt.plot(dates_df, results_maxsr['sharpe_ratio_diff'], label="Max Sharpe",␣
↪color='blue', linewidth=2.5)
plt.plot(dates_df, results_minvar['sharpe_ratio_diff'], label="Min Variance",␣
↪color='red', linewidth=2.5)
plt.ylabel("$\Delta$ Sharpe ratio")
plt.title("Sharpe ratio difference of Optimised Portfolio against Benchmark")
plt.xticks(rotation=45)
plt.legend()
plt.show()
```


Volatility difference of Optimised Portfolio against Benchmark
Max Sharpe
Min Variance
Δ Volatility (%)
4
3
2
1
0
−1
−2
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11


Return difference of Optimised Portfolio against Benchmark
Max Sharpe
Min Variance
Δ Return (%)
4
2
0
−2
−4
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11



Sharpe ratio difference of Optimised Portfolio against Benchmark
Max Sharpe
Min Variance
Δ Sharpe ratio
3
2
1
0
−1
−2
−3
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11