1[without risk free]

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4 1. Pick any 10 risky assets from the market. Use their 3 months closing price to obtain simple returns.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas_datareader as web
!wget https://raw.githubusercontent.com/qoo121314/Portfolio_Optimizer/master/
↪PortfolioOptimizer.py
```

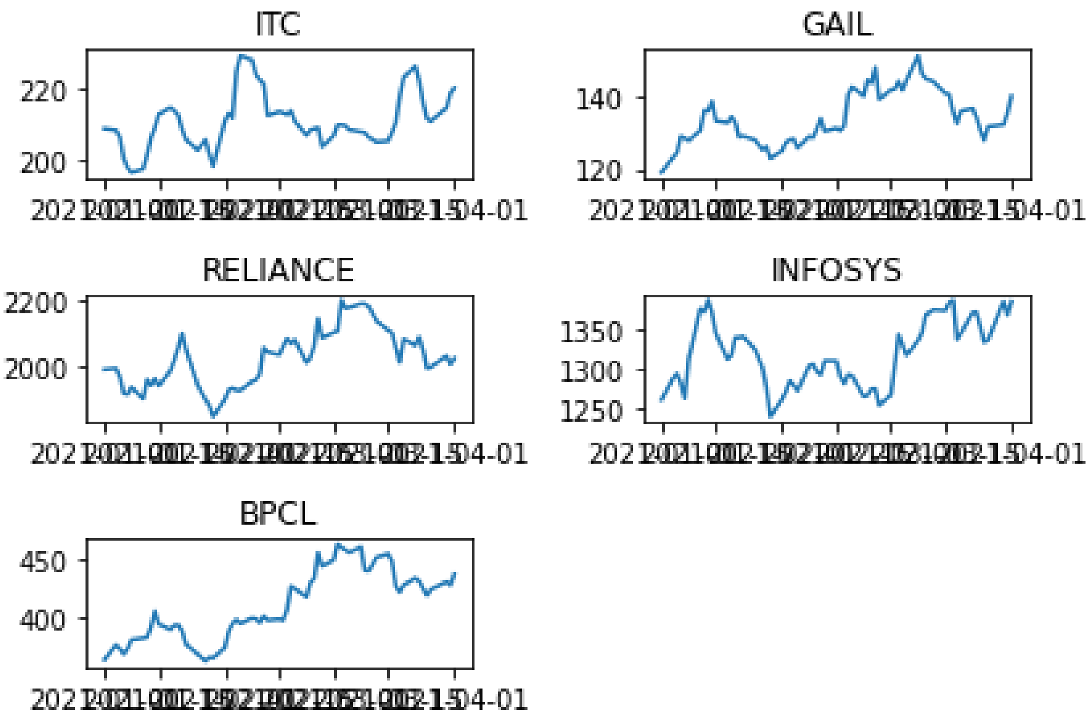
```
--2021-04-10 20:21:07--  https://raw.githubusercontent.com/qoo121314/Portfolio_O
ptimizer/master/PortfolioOptimizer.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)…
185.199.108.133, 185.199.109.133, 185.199.110.133, …
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 21688 (21K) [text/plain]
Saving to: 'PortfolioOptimizer.py'

PortfolioOptimizer. 100%[===================>]  21.18K  --.-KB/s    in 0s

2021-04-10 20:21:07 (83.5 MB/s) - 'PortfolioOptimizer.py' saved [21688/21688]
```

[2]:
```
tickers1 = ["ITC.NS", "GAIL.NS","RELIANCE.NS", "INFY.NS", "BPCL.NS"] #
tickers2 =  ["WIPRO.NS", "TCS.NS", "HDFCBANK.NS", "KOTAKBANK.NS", "LT.NS"]
```

[3]:
```
multpl_stocks_1 = web.get_data_yahoo(tickers1,
start = "2021-01-01",
```

```
end = "2021-03-31")
multpl_stocks_2 = web.get_data_yahoo(tickers2,
start = "2021-01-01",
end = "2021-03-31")
```

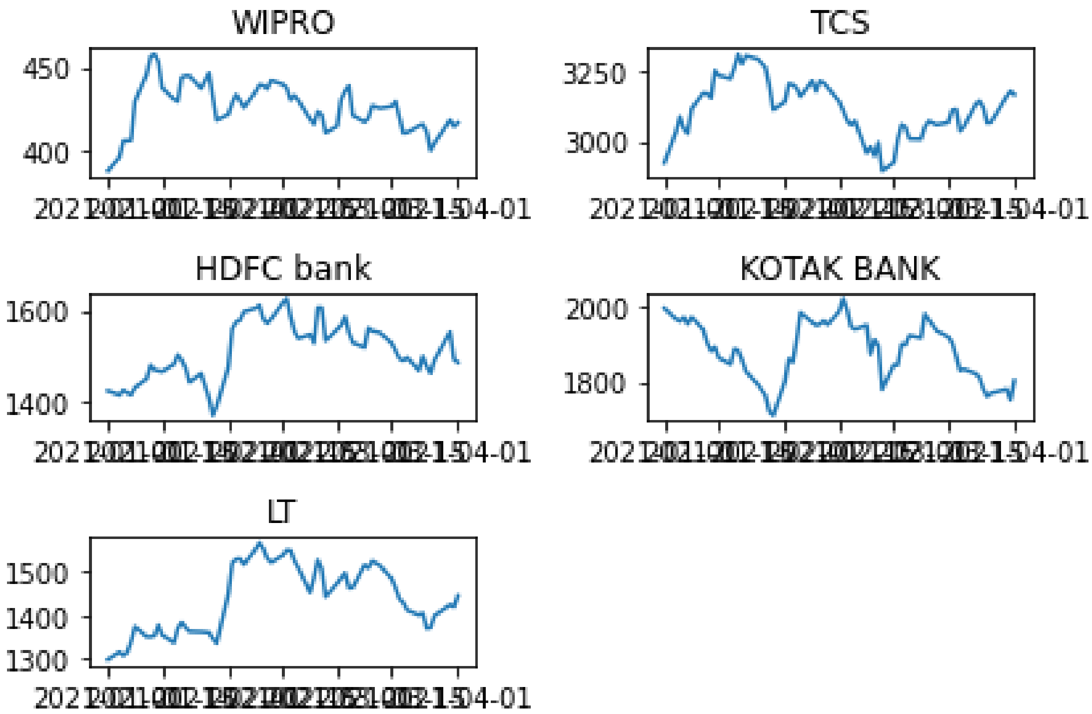
[4]:
```
fig = plt.figure()

ax1 = fig.add_subplot(321)
ax2 = fig.add_subplot(322)
ax3 = fig.add_subplot(323)
ax4 = fig.add_subplot(324)
ax5 = fig.add_subplot(325)


ax1.plot(multpl_stocks_1['Adj Close']['ITC.NS'])
ax1.set_title("ITC")

ax2.plot(multpl_stocks_1['Adj Close']['GAIL.NS'])
ax2.set_title("GAIL")

ax3.plot(multpl_stocks_1['Adj Close']['RELIANCE.NS'])
ax3.set_title("RELIANCE")

ax4.plot(multpl_stocks_1['Adj Close']['INFY.NS'])
ax4.set_title("INFOSYS")

ax5.plot(multpl_stocks_1['Adj Close']['BPCL.NS'])
ax5.set_title("BPCL")

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



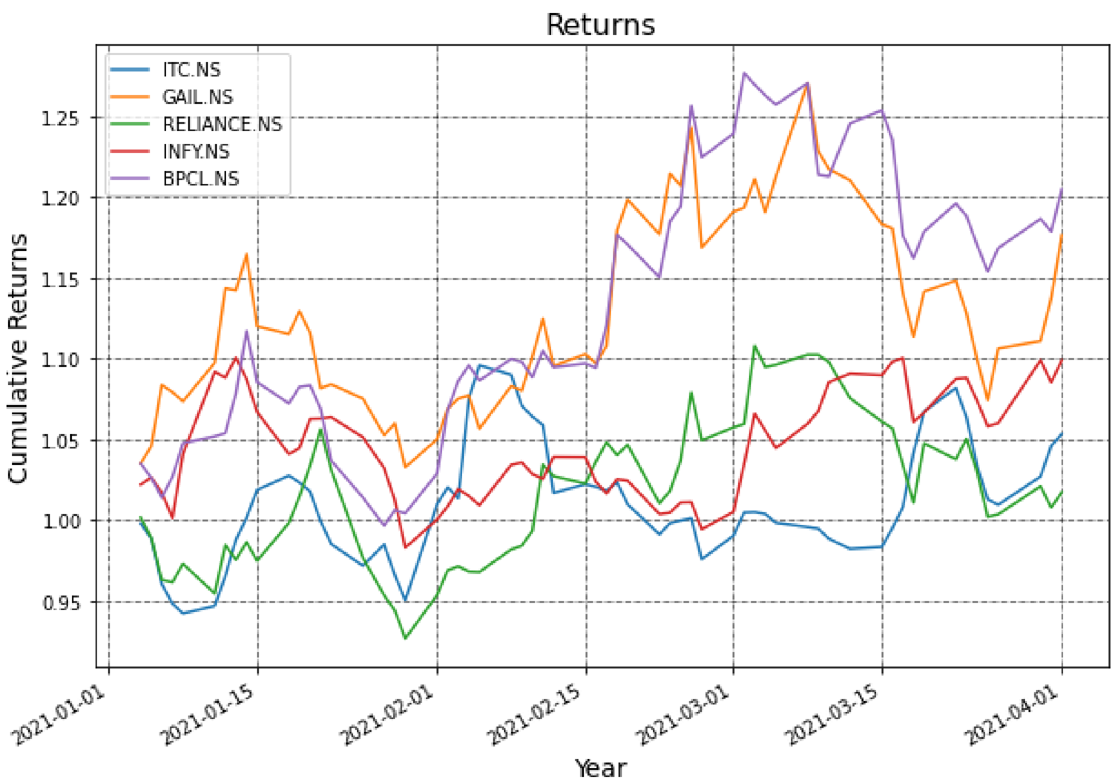
[5]:

```
fig = plt.figure()
ax6 = fig.add_subplot(321)
ax7 = fig.add_subplot(322)
ax8 = fig.add_subplot(323)
ax9 = fig.add_subplot(324)
ax10 = fig.add_subplot(325)

ax6.plot(multpl_stocks_2['Adj Close']['WIPRO.NS'])
ax6.set_title("WIPRO")

ax7.plot(multpl_stocks_2['Adj Close']['TCS.NS'])
ax7.set_title("TCS")

ax8.plot(multpl_stocks_2['Adj Close']['HDFCBANK.NS'])
ax8.set_title("HDFC bank")

ax9.plot(multpl_stocks_2['Adj Close']['KOTAKBANK.NS'])
ax9.set_title("KOTAK BANK")

ax10.plot(multpl_stocks_2['Adj Close']['LT.NS'])
ax10.set_title("LT")

plt.tight_layout()
```

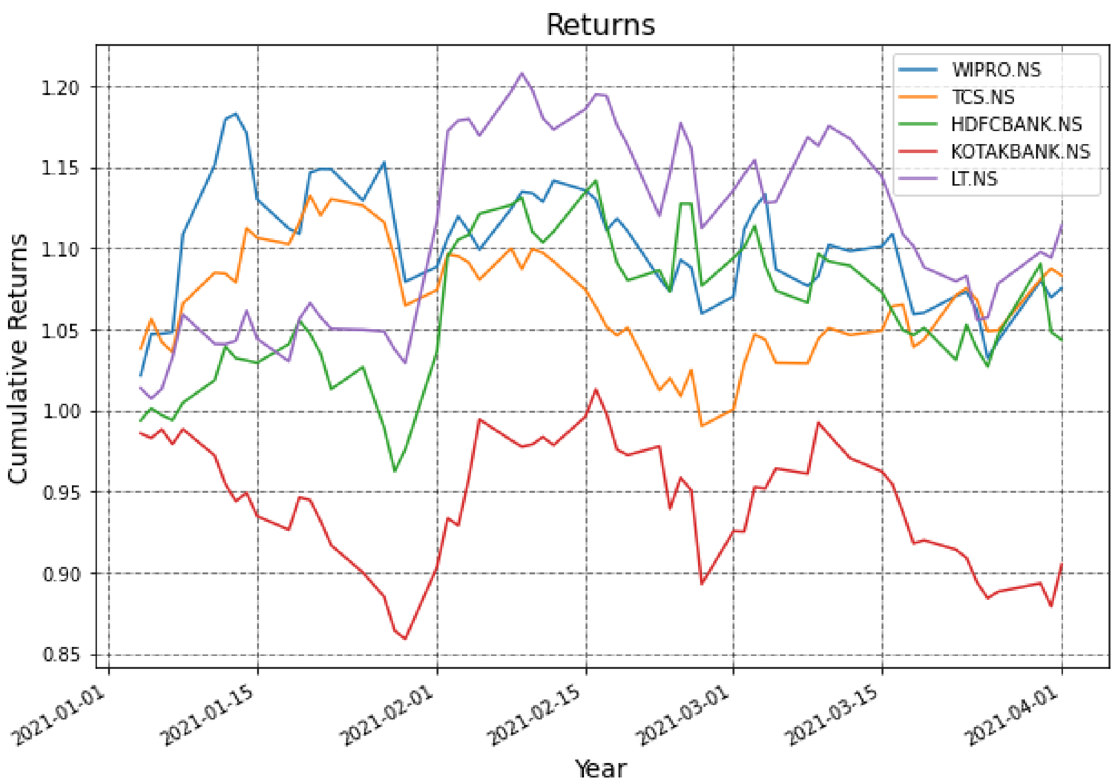
```
plt.show()
```



[6]:
```
# Plot all the close prices
((multpl_stocks_1['Adj Close'].pct_change()+1).cumprod()).plot(figsize=(10, 7))

# Show the legend
plt.legend()

# Define the label for the title of the figure
plt.title("Returns", fontsize=16)

# Define the labels for x-axis and y-axis
plt.ylabel('Cumulative Returns', fontsize=14)
plt.xlabel('Year', fontsize=14)

# Plot the grid lines
plt.grid(which="major", color='k', linestyle='-.', linewidth=0.5)
plt.show()
```

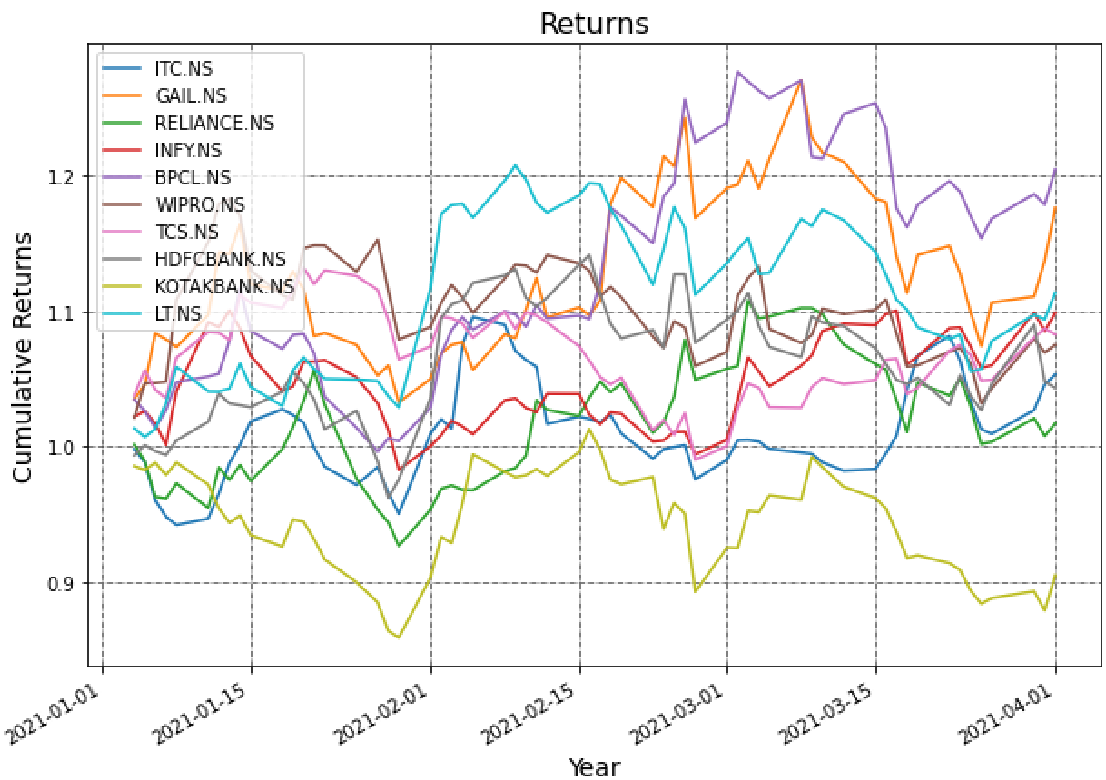


[7]:
```
# Plot all the close prices
((multpl_stocks_2['Adj Close'].pct_change()+1).cumprod()).plot(figsize=(10, 7))

# Show the legend
plt.legend()

# Define the label for the title of the figure
plt.title("Returns", fontsize=16)

# Define the labels for x-axis and y-axis
plt.ylabel('Cumulative Returns', fontsize=14)
plt.xlabel('Year', fontsize=14)

# Plot the grid lines
plt.grid(which="major", color='k', linestyle='-.', linewidth=0.5)
plt.show()
```



[8]:
```
tickers = ["ITC.NS", "GAIL.NS","RELIANCE.NS", "INFY.NS", "BPCL.NS", "WIPRO.NS",␣
↪"TCS.NS", "HDFCBANK.NS", "KOTAKBANK.NS", "LT.NS"]


multpl_stocks = web.get_data_yahoo(tickers,
start = "2021-01-01",
end = "2021-03-31")




# Plot all the close prices
((multpl_stocks['Adj Close'].pct_change()+1).cumprod()).plot(figsize=(10, 7))

# Show the legend
plt.legend()

# Define the label for the title of the figure
plt.title("Returns", fontsize=16)

# Define the labels for x-axis and y-axis
plt.ylabel('Cumulative Returns', fontsize=14)
```

```python
plt.xlabel('Year', fontsize=14)

# Plot the grid lines
plt.grid(which="major", color='k', linestyle='-.', linewidth=0.5)
plt.show()
```



[8]:

```python

```

5 2. Use the mean-variance theory and build the Markowitz efficient frontier.

[9]:

```python
stocks = multpl_stocks['Adj Close']
```

[10]:

```python
stocks.head()
```

[10]:

```
Symbols         ITC.NS     GAIL.NS  …  KOTAKBANK.NS        LT.NS
Date                                …
2021-01-01  208.898636  119.134895  …   1994.050049  1297.000000
2021-01-04  208.459045  123.326057  …   1965.550049  1314.599976
2021-01-05  206.554199  124.578583  …   1959.750000  1306.300049
2021-01-06  200.644272  129.106964  …   1970.400024  1314.000000
```

```
2021-01-07  198.104477  128.577042  …   1952.400024  1338.949951

[5 rows x 10 columns]
```

[11]:
```
# Converting everything to logarithmic returns is simple. Think of it as the␣
↪log of an arithmetic daily return (which is obtained by dividing the price␣
↪at day n, by the price at day n-1).
```

[12]:
```
log_returns = np.log(stocks/stocks.shift(1))
# log_returns.dropna(inplace=True)
log_returns.head()
```

[12]:
```
Symbols       ITC.NS   GAIL.NS  …  KOTAKBANK.NS     LT.NS
Date                            …
2021-01-01       NaN       NaN  …           NaN       NaN
2021-01-04 -0.002107  0.034575  …     -0.014396  0.013479
2021-01-05 -0.009180  0.010105  …     -0.002955 -0.006334
2021-01-06 -0.029029  0.035705  …      0.005420  0.005877
2021-01-07 -0.012739 -0.004113  …     -0.009177  0.018810

[5 rows x 10 columns]
```

[13]:
```
# I'm going to use 6000 portfolios, but feel free to use less if your computer␣
↪is too slow. The random seed at the top of the code is making sure I get the␣
↪same random numbers every time for reproducibility.
```

[14]:
```
np.random.seed(30)
num_ports = 6000
all_weights = np.zeros((num_ports, len(stocks.columns)))
ret_arr = np.zeros(num_ports)
vol_arr = np.zeros(num_ports)
sharpe_arr = np.zeros(num_ports)

for x in range(num_ports):
    # Weights
    weights = np.array(np.random.random(10))
    weights = weights/np.sum(weights) # Wi*

    # Save weights
    all_weights[x,:] = weights

    # Expected return
    ret_arr[x] = np.sum( (log_returns.mean() * weights * 252))

    # Expected volatility
    vol_arr[x] = np.sqrt(np.dot(weights.T, np.dot(log_returns.cov()*252,␣
↪weights)))
```

```
    # Sharpe Ratio
    sharpe_arr[x] = ret_arr[x]/vol_arr[x]
```

[15]:
```
print("Max Sharpe")
print(sharpe_arr.max())
print("\n\n")
print("location in array")
print(sharpe_arr.argmax())
```

```
Max Sharpe
2.1829045591482688



location in array
5829
```

[16]:
```
# Print the allocations in the max result
print(all_weights[5829,:])
max_returns = ret_arr[sharpe_arr.argmax()]
max_vol = vol_arr[sharpe_arr.argmax()]
```

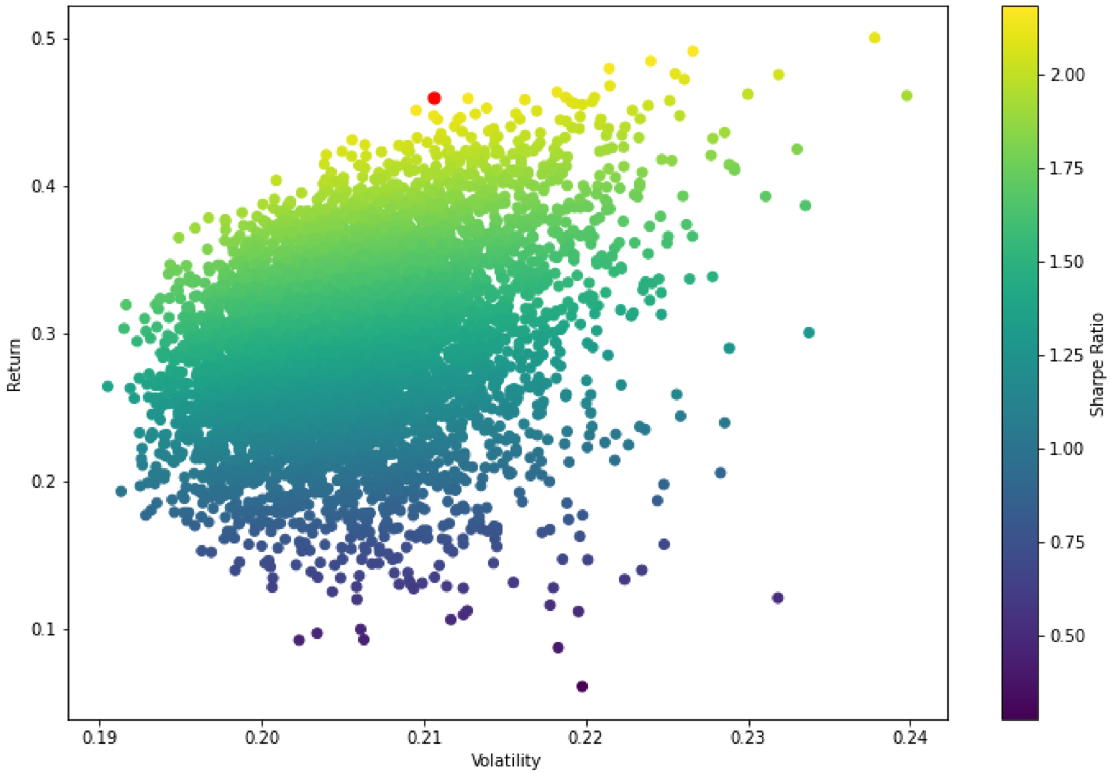
```
[0.16018557 0.16545621 0.01349526 0.12533042 0.20906412 0.01196343
 0.0928393  0.10107981 0.00231196 0.11827392]
```

[17]:
```
for i in range(10):
  print("The allocation for: "+str(tickers[i])+" is: "+ str(all_weights[5829,:
 ↪][i]))
```

```
The allocation for: ITC.NS is: 0.16018557420080826
The allocation for: GAIL.NS is: 0.16545621356234136
The allocation for: RELIANCE.NS is: 0.013495255325259 86
The allocation for: INFY.NS is: 0.12533041875814782
The allocation for: BPCL.NS is: 0.20906411879687964
The allocation for: WIPRO.NS is: 0.011963429222867 24
The allocation for: TCS.NS is: 0.09283929590658799
The allocation for: HDFCBANK.NS is: 0.10107981312449213
The allocation for: KOTAKBANK.NS is: 0.002311956828650832
The allocation for: LT.NS is: 0.11827392427396483
```

[18]:
```
plt.figure(figsize=(12,8))
plt.scatter(vol_arr, ret_arr, c=sharpe_arr, cmap='viridis')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.scatter(max_vol, max_returns,c='red', s=50) # red dot
```

```
plt.show()
```



[19]:

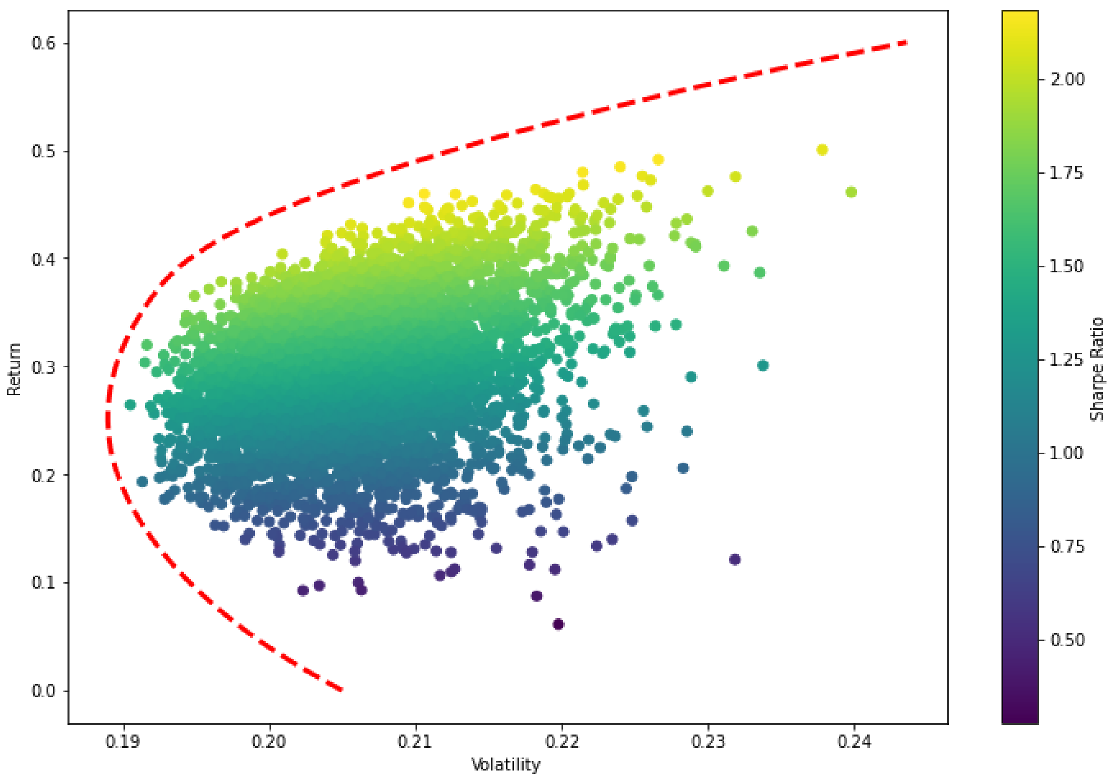
```
def get_ret_vol_sr(weights):
    weights = np.array(weights)
    ret = np.sum(log_returns.mean() * weights) * 252
    vol = np.sqrt(np.dot(weights.T, np.dot(log_returns.cov()*252, weights)))
    sr = ret/vol
    return np.array([ret, vol, sr])

def neg_sharpe(weights):
# the number 2 is the sharpe ratio index from the get_ret_vol_sr
    return get_ret_vol_sr(weights)[2] * -1

def check_sum(weights):
    #return 0 if sum of the weights is 1
    return np.sum(weights)-1

def minimize_volatility(weights):
  return get_ret_vol_sr(weights)[1]
```

[20]:

```
frontier_x = []
frontier_y = np.linspace(0,0.6,200)
```

```
from scipy.optimize import minimize
bounds = ((0,1),(0,1),(0,1),(0,1),(0,1),(0,1),(0,1),(0,1),(0,1),(0,1))
init_guess = [0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50,0.50]

for possible_return in frontier_y:
    cons = ({'type':'eq', 'fun':check_sum},
            {'type':'eq', 'fun': lambda w: get_ret_vol_sr(w)[0] -␣
 ↪possible_return})

    result = minimize(minimize_volatility,init_guess,method='SLSQP',␣
 ↪bounds=bounds, constraints=cons)
    frontier_x.append(result['fun'])
```

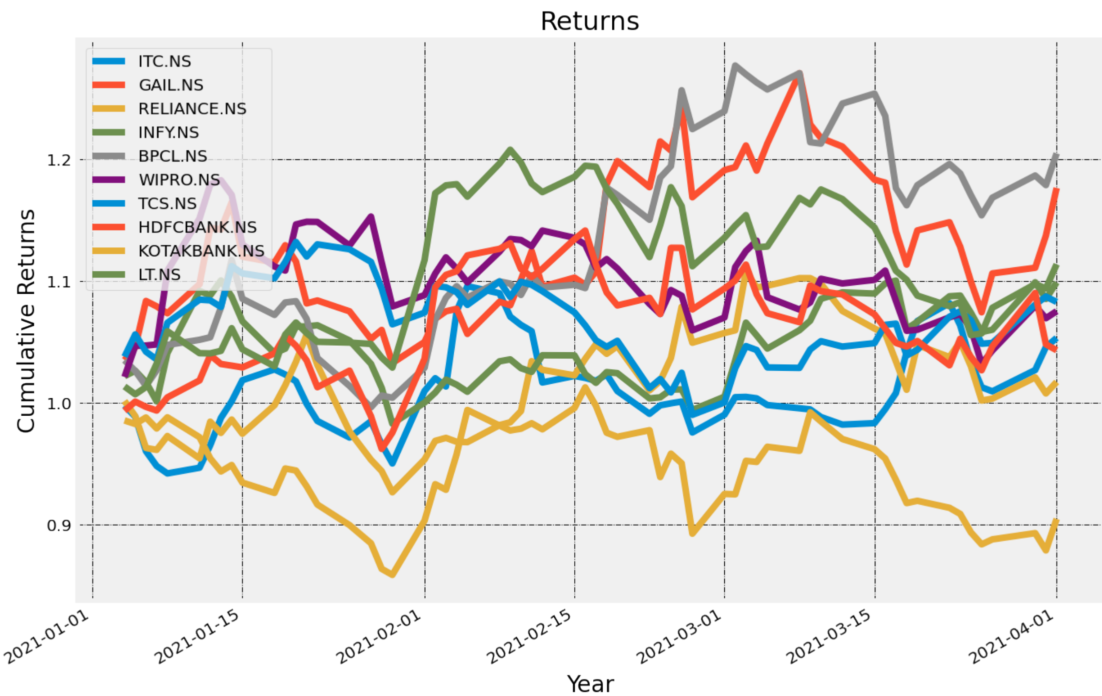
[21]:
```
plt.figure(figsize=(12,8))
plt.scatter(vol_arr, ret_arr, c=sharpe_arr, cmap='viridis')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.plot(frontier_x,frontier_y, 'r--', linewidth=3)
plt.savefig('cover.png')
plt.show()
```



6 Different Methodology

[22]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import scipy.optimize as sco

plt.style.use('fivethirtyeight')
np.random.seed(777)

%matplotlib inline
%config InlineBackend.figure_format = 'retina'
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas_datareader as web
tickers = ["ITC.NS", "GAIL.NS","RELIANCE.NS", "INFY.NS", "BPCL.NS", "WIPRO.NS",␣
 ↪"TCS.NS", "HDFCBANK.NS", "KOTAKBANK.NS", "LT.NS"]


multpl_stocks = web.get_data_yahoo(tickers,
start = "2021-01-01",
end = "2021-03-31")





# Plot all the close prices
((multpl_stocks['Adj Close'].pct_change()+1).cumprod()).plot(figsize=(10, 7))

# Show the legend
plt.legend()

# Define the label for the title of the figure
plt.title("Returns", fontsize=16)

# Define the labels for x-axis and y-axis
plt.ylabel('Cumulative Returns', fontsize=14)
plt.xlabel('Year', fontsize=14)

# Plot the grid lines
plt.grid(which="major", color='k', linestyle='-.', linewidth=0.5)
plt.show()
```

```
stocks = multpl_stocks['Adj Close']
```

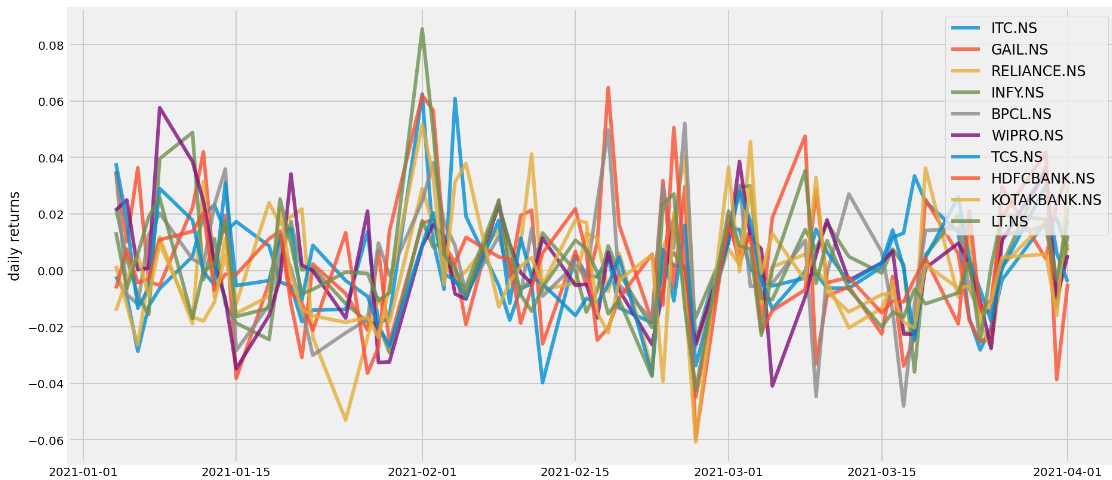


[23]:
```
stocks.head()
```

[23]:
```
Symbols         ITC.NS     GAIL.NS  …  KOTAKBANK.NS        LT.NS
Date                                …
2021-01-01  208.898636  119.134895  …   1994.050049  1297.000000
2021-01-04  208.459045  123.326057  …   1965.550049  1314.599976
2021-01-05  206.554199  124.578583  …   1959.750000  1306.300049
2021-01-06  200.644272  129.106964  …   1970.400024  1314.000000
2021-01-07  198.104477  128.577042  …   1952.400024  1338.949951

[5 rows x 10 columns]
```

[24]:
```
returns = stocks.pct_change()

plt.figure(figsize=(14, 7))
for c in returns.columns.values:
    plt.plot(returns.index, returns[c], lw=3, alpha=0.8,label=c)
plt.legend(loc='upper right', fontsize=12)
plt.ylabel('daily returns')
```

[24]:
```
Text(0, 0.5, 'daily returns')
```



[25]:

```
def portfolio_annualised_performance(weights, mean_returns, cov_matrix):
    returns = np.sum(mean_returns*weights ) *252
    std = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights))) * np.sqrt(252)
    return std, returns
def random_portfolios(num_portfolios, mean_returns, cov_matrix, risk_free_rate):
    results = np.zeros((10,num_portfolios))
    weights_record = []
    for i in range(num_portfolios):
        weights = np.random.random(10)
        weights /= np.sum(weights)
        weights_record.append(weights)
        portfolio_std_dev, portfolio_return =␣
 ↪portfolio_annualised_performance(weights, mean_returns, cov_matrix)
        results[0,i] = portfolio_std_dev
        results[1,i] = portfolio_return
        results[2,i] = (portfolio_return - risk_free_rate) / portfolio_std_dev
    return results, weights_record
```

[26]:

```
returns = stocks.pct_change()
mean_returns = returns.mean()
cov_matrix = returns.cov()
num_portfolios = 25000
risk_free_rate = 0.0178
```

[27]:

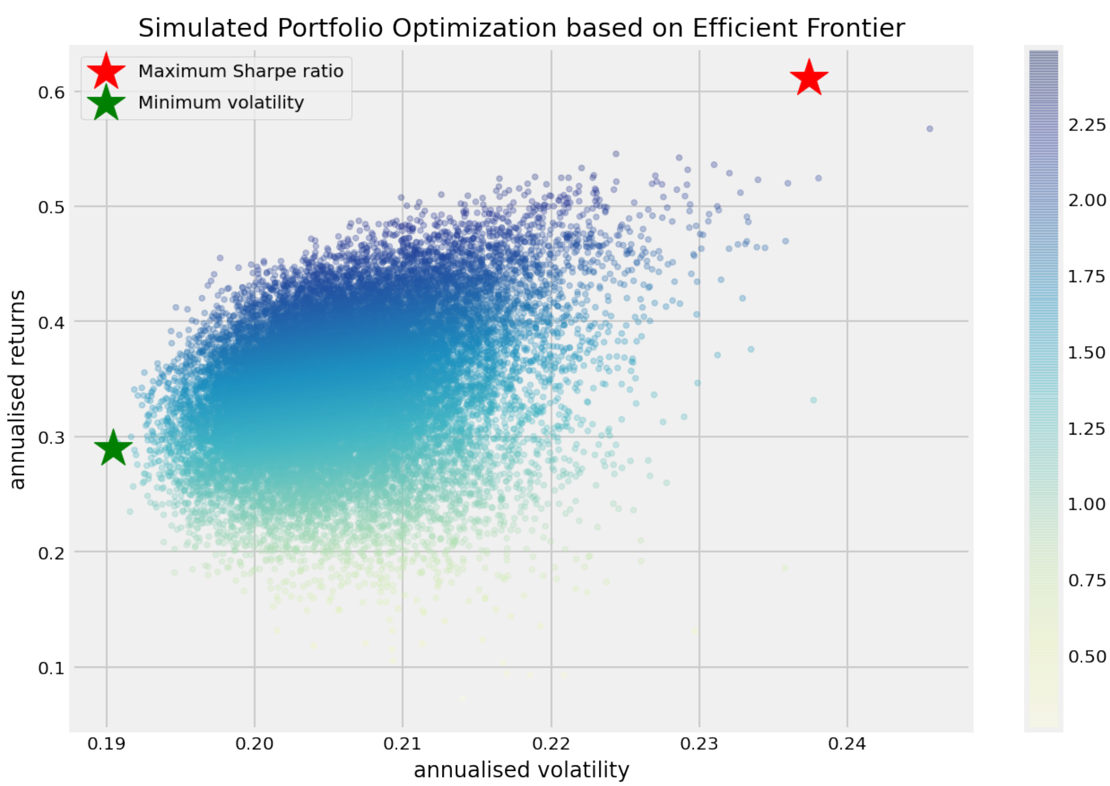
```
def display_simulated_ef_with_random(mean_returns, cov_matrix, num_portfolios,␣
 ↪risk_free_rate):
    results, weights = random_portfolios(num_portfolios,mean_returns,␣
 ↪cov_matrix, risk_free_rate)

    max_sharpe_idx = np.argmax(results[2])
```

```
    sdp, rp = results[0,max_sharpe_idx], results[1,max_sharpe_idx]
    max_sharpe_allocation = pd.DataFrame(weights[max_sharpe_idx],index=stocks.
↪columns,columns=['allocation'])
    max_sharpe_allocation.allocation = [round(i*100,2)for i in␣
↪max_sharpe_allocation.allocation]
    max_sharpe_allocation = max_sharpe_allocation.T

    min_vol_idx = np.argmin(results[0])
    sdp_min, rp_min = results[0,min_vol_idx], results[1,min_vol_idx]
    min_vol_allocation = pd.DataFrame(weights[min_vol_idx],index=stocks.
↪columns,columns=['allocation'])
    min_vol_allocation.allocation = [round(i*100,2)for i in min_vol_allocation.
↪allocation]
    min_vol_allocation = min_vol_allocation.T

    print ("-"*80)
    print ("Maximum Sharpe Ratio Portfolio Allocation\n")
    print ("Annualised Return:", round(rp,2))
    print ("Annualised Volatility:", round(sdp,2))
    print ("\n")
    print (max_sharpe_allocation)
    print ("-"*80)
    print ("Minimum Volatility Portfolio Allocation\n")
    print ("Annualised Return:", round(rp_min,2))
    print ("Annualised Volatility:", round(sdp_min,2))
    print ("\n")
    print (min_vol_allocation)

    plt.figure(figsize=(10, 7))
    plt.scatter(results[0,:],results[1,:],c=results[2,:],cmap='YlGnBu',␣
↪marker='o', s=10, alpha=0.3)
    plt.colorbar()
    plt.scatter(sdp,rp,marker='*',color='r',s=500, label='Maximum Sharpe ratio')
    plt.scatter(sdp_min,rp_min,marker='*',color='g',s=500, label='Minimum␣
↪volatility')
    plt.title('Simulated Portfolio Optimization based on Efficient Frontier')
    plt.xlabel('annualised volatility')
    plt.ylabel('annualised returns')
    plt.legend(labelspacing=0.8)
```

[28]:
```
display_simulated_ef_with_random(mean_returns, cov_matrix, num_portfolios,␣
↪risk_free_rate)
```

```
--------------------------------------------------------------------------------
Maximum Sharpe Ratio Portfolio Allocation

Annualised Return: 0.61
```

```
Annualised Volatility: 0.24


Symbols     ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation    1.46    12.27         2.56  …         0.91          0.24   6.64

[1 rows x 10 columns]
--------------------------------------------------------------------------------
Minimum Volatility Portfolio Allocation

Annualised Return: 0.29
Annualised Volatility: 0.19


Symbols     ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation   20.95     0.76         9.14  …         7.13         10.03   1.84

[1 rows x 10 columns]
```



[29]:
```python
table = stocks
def neg_sharpe_ratio(weights, mean_returns, cov_matrix, risk_free_rate):
```

```
    p_var, p_ret = portfolio_annualised_performance(weights, mean_returns,␣
↪cov_matrix)
    return -(p_ret - risk_free_rate) / p_var

def max_sharpe_ratio(mean_returns, cov_matrix, risk_free_rate):
    num_assets = len(mean_returns)
    args = (mean_returns, cov_matrix, risk_free_rate)
    constraints = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1})
    bound = (0.0,1.0)
    bounds = tuple(bound for asset in range(num_assets))
    result = sco.minimize(neg_sharpe_ratio, num_assets*[1./num_assets,],␣
↪args=args,
                        method='SLSQP', bounds=bounds, constraints=constraints)
    return result
```

[30]:

```
def portfolio_volatility(weights, mean_returns, cov_matrix):
    return portfolio_annualised_performance(weights, mean_returns,␣
↪cov_matrix)[0]

def min_variance(mean_returns, cov_matrix):
    num_assets = len(mean_returns)
    args = (mean_returns, cov_matrix)
    constraints = ({'type': 'eq', 'fun': lambda x: np.sum(x) - 1})
    bound = (0.0,1.0)
    bounds = tuple(bound for asset in range(num_assets))

    result = sco.minimize(portfolio_volatility, num_assets*[1./num_assets,],␣
↪args=args,
                        method='SLSQP', bounds=bounds, constraints=constraints)

    return result
```

[31]:

```
def efficient_return(mean_returns, cov_matrix, target):
    num_assets = len(mean_returns)
    args = (mean_returns, cov_matrix)

    def portfolio_return(weights):
        return portfolio_annualised_performance(weights, mean_returns,␣
↪cov_matrix)[1]

    constraints = ({'type': 'eq', 'fun': lambda x: portfolio_return(x) -␣
↪target},
                   {'type': 'eq', 'fun': lambda x: np.sum(x) - 1})
    bounds = tuple((0,1) for asset in range(num_assets))
    result = sco.minimize(portfolio_volatility, num_assets*[1./num_assets,],␣
↪args=args, method='SLSQP', bounds=bounds, constraints=constraints)
```

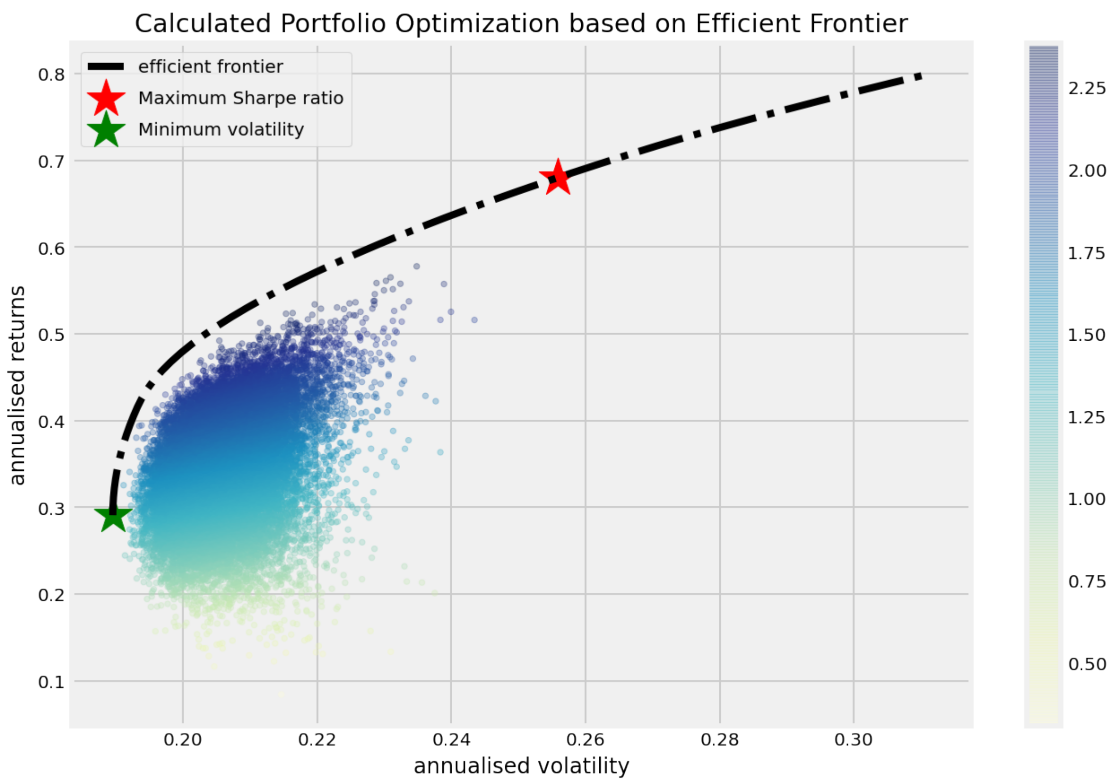
```
    return result


def efficient_frontier(mean_returns, cov_matrix, returns_range):
    efficients = []
    for ret in returns_range:
        efficients.append(efficient_return(mean_returns, cov_matrix, ret))
    return efficients
```

[32]:
```
def display_calculated_ef_with_random(mean_returns, cov_matrix, num_portfolios,␣
↪risk_free_rate):
    results, _ = random_portfolios(num_portfolios,mean_returns, cov_matrix,␣
↪risk_free_rate)

    max_sharpe = max_sharpe_ratio(mean_returns, cov_matrix, risk_free_rate)
    sdp, rp = portfolio_annualised_performance(max_sharpe['x'], mean_returns,␣
↪cov_matrix)
    max_sharpe_allocation = pd.DataFrame(max_sharpe.x,index=table.
↪columns,columns=['allocation'])
    max_sharpe_allocation.allocation = [round(i*100,2)for i in␣
↪max_sharpe_allocation.allocation]
    max_sharpe_allocation = max_sharpe_allocation.T
    max_sharpe_allocation

    min_vol = min_variance(mean_returns, cov_matrix)
    sdp_min, rp_min = portfolio_annualised_performance(min_vol['x'],␣
↪mean_returns, cov_matrix)
    min_vol_allocation = pd.DataFrame(min_vol.x,index=table.
↪columns,columns=['allocation'])
    min_vol_allocation.allocation = [round(i*100,2)for i in min_vol_allocation.
↪allocation]
    min_vol_allocation = min_vol_allocation.T

    print ("-"*80)
    print ("Maximum Sharpe Ratio Portfolio Allocation\n")
    print ("Annualised Return:", round(rp,2))
    print ("Annualised Volatility:", round(sdp,2))
    print ("\n")
    print (max_sharpe_allocation)
    print ("-"*80)
    print ("Minimum Volatility Portfolio Allocation\n")
    print ("Annualised Return:", round(rp_min,2))
    print ("Annualised Volatility:", round(sdp_min,2))
    print ("\n")
    print (min_vol_allocation)
```

```
    plt.figure(figsize=(10, 7))
    plt.scatter(results[0,:],results[1,:],c=results[2,:],cmap='YlGnBu',␣
↪marker='o', s=10, alpha=0.3)
    plt.colorbar()
    plt.scatter(sdp,rp,marker='*',color='r',s=500, label='Maximum Sharpe ratio')
    plt.scatter(sdp_min,rp_min,marker='*',color='g',s=500, label='Minimum␣
↪volatility')

    target = np.linspace(rp_min, 0.8, 50)
    efficient_portfolios = efficient_frontier(mean_returns, cov_matrix, target)
    plt.plot([p['fun'] for p in efficient_portfolios], target, linestyle='-.',␣
↪color='black', label='efficient frontier')
    plt.title('Calculated Portfolio Optimization based on Efficient Frontier')
    plt.xlabel('annualised volatility')
    plt.ylabel('annualised returns')
    plt.legend(labelspacing=0.8)
```

[33]:
```
display_calculated_ef_with_random(mean_returns, cov_matrix, num_portfolios,␣
↪risk_free_rate)
```

```
--------------------------------------------------------------------------------
Maximum Sharpe Ratio Portfolio Allocation

Annualised Return: 0.68
Annualised Volatility: 0.26


Symbols      ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation     3.37    10.47          0.0  …          0.0           0.0   7.19

[1 rows x 10 columns]
--------------------------------------------------------------------------------
Minimum Volatility Portfolio Allocation

Annualised Return: 0.29
Annualised Volatility: 0.19


Symbols      ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation    22.92     1.57         5.02  …         6.77         12.43    0.0

[1 rows x 10 columns]
```

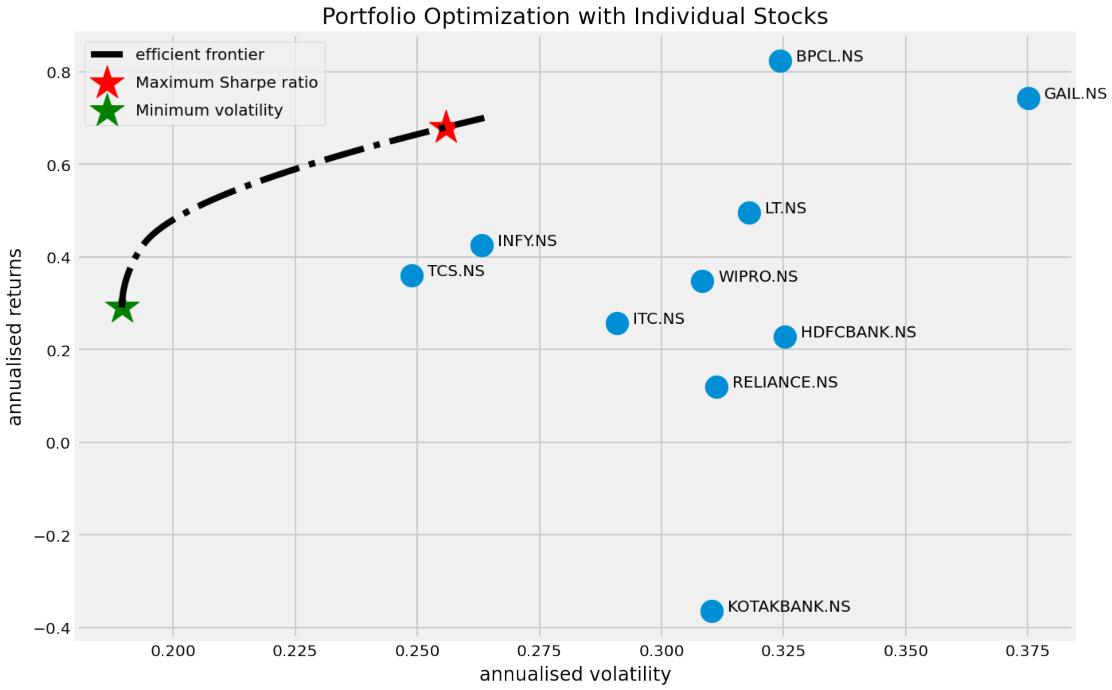


[34]:
```
def display_ef_with_selected(mean_returns, cov_matrix, risk_free_rate):
    max_sharpe = max_sharpe_ratio(mean_returns, cov_matrix, risk_free_rate)
    sdp, rp = portfolio_annualised_performance(max_sharpe['x'], mean_returns,␣
↪cov_matrix)
    max_sharpe_allocation = pd.DataFrame(max_sharpe.x,index=table.
↪columns,columns=['allocation'])
    max_sharpe_allocation.allocation = [round(i*100,2)for i in␣
↪max_sharpe_allocation.allocation]
    max_sharpe_allocation = max_sharpe_allocation.T
    max_sharpe_allocation

    min_vol = min_variance(mean_returns, cov_matrix)
    sdp_min, rp_min = portfolio_annualised_performance(min_vol['x'],␣
↪mean_returns, cov_matrix)
    min_vol_allocation = pd.DataFrame(min_vol.x,index=table.
↪columns,columns=['allocation'])
    min_vol_allocation.allocation = [round(i*100,2)for i in min_vol_allocation.
↪allocation]
    min_vol_allocation = min_vol_allocation.T

    an_vol = np.std(returns) * np.sqrt(252)
    an_rt = mean_returns * 252
```

```
    print ("-"*80)
    print ("Maximum Sharpe Ratio Portfolio Allocation\n")
    print ("Annualised Return:", round(rp,2))
    print ("Annualised Volatility:", round(sdp,2))
    print ("\n")
    print (max_sharpe_allocation)
    print ("-"*80)
    print ("Minimum Volatility Portfolio Allocation\n")
    print ("Annualised Return:", round(rp_min,2))
    print ("Annualised Volatility:", round(sdp_min,2))
    print ("\n")
    print (min_vol_allocation)
    print ("-"*80)
    print ("Individual Stock Returns and Volatility\n")
    for i, txt in enumerate(table.columns):
      print (txt,":","annuaised return",round(an_rt[i],2),", annualised␣
↪volatility:",round(an_vol[i],2))
    print ("-"*80)

    fig, ax = plt.subplots(figsize=(10, 7))
    ax.scatter(an_vol,an_rt,marker='o',s=200)

    for i, txt in enumerate(table.columns):
        ax.annotate(txt, (an_vol[i],an_rt[i]), xytext=(10,0),␣
↪textcoords='offset points')
    ax.scatter(sdp,rp,marker='*',color='r',s=500, label='Maximum Sharpe ratio')
    ax.scatter(sdp_min,rp_min,marker='*',color='g',s=500, label='Minimum␣
↪volatility')

    target = np.linspace(rp_min, 0.7, 50)
    efficient_portfolios = efficient_frontier(mean_returns, cov_matrix, target)
    ax.plot([p['fun'] for p in efficient_portfolios], target, linestyle='-.',␣
↪color='black', label='efficient frontier')
    ax.set_title('Portfolio Optimization with Individual Stocks')
    ax.set_xlabel('annualised volatility')
    ax.set_ylabel('annualised returns')
    ax.legend(labelspacing=0.8)
display_ef_with_selected(mean_returns, cov_matrix, risk_free_rate)
```

```
--------------------------------------------------------------------------------
Maximum Sharpe Ratio Portfolio Allocation

Annualised Return: 0.68
Annualised Volatility: 0.26
```

```
Symbols     ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation    3.37    10.47          0.0  …          0.0           0.0   7.19

[1 rows x 10 columns]
--------------------------------------------------------------------------------
Minimum Volatility Portfolio Allocation

Annualised Return: 0.29
Annualised Volatility: 0.19


Symbols     ITC.NS  GAIL.NS  RELIANCE.NS  …  HDFCBANK.NS  KOTAKBANK.NS  LT.NS
allocation   22.92     1.57         5.02  …         6.77         12.43    0.0

[1 rows x 10 columns]
--------------------------------------------------------------------------------
Individual Stock Returns and Volatility

ITC.NS : annuaised return 0.26 , annualised volatility: 0.29
GAIL.NS : annuaised return 0.74 , annualised volatility: 0.38
RELIANCE.NS : annuaised return 0.12 , annualised volatility: 0.31
INFY.NS : annuaised return 0.42 , annualised volatility: 0.26
BPCL.NS : annuaised return 0.82 , annualised volatility: 0.32
WIPRO.NS : annuaised return 0.35 , annualised volatility: 0.31
TCS.NS : annuaised return 0.36 , annualised volatility: 0.25
HDFCBANK.NS : annuaised return 0.23 , annualised volatility: 0.33
KOTAKBANK.NS : annuaised return -0.36 , annualised volatility: 0.31
LT.NS : annuaised return 0.5 , annualised volatility: 0.32
--------------------------------------------------------------------------------
```



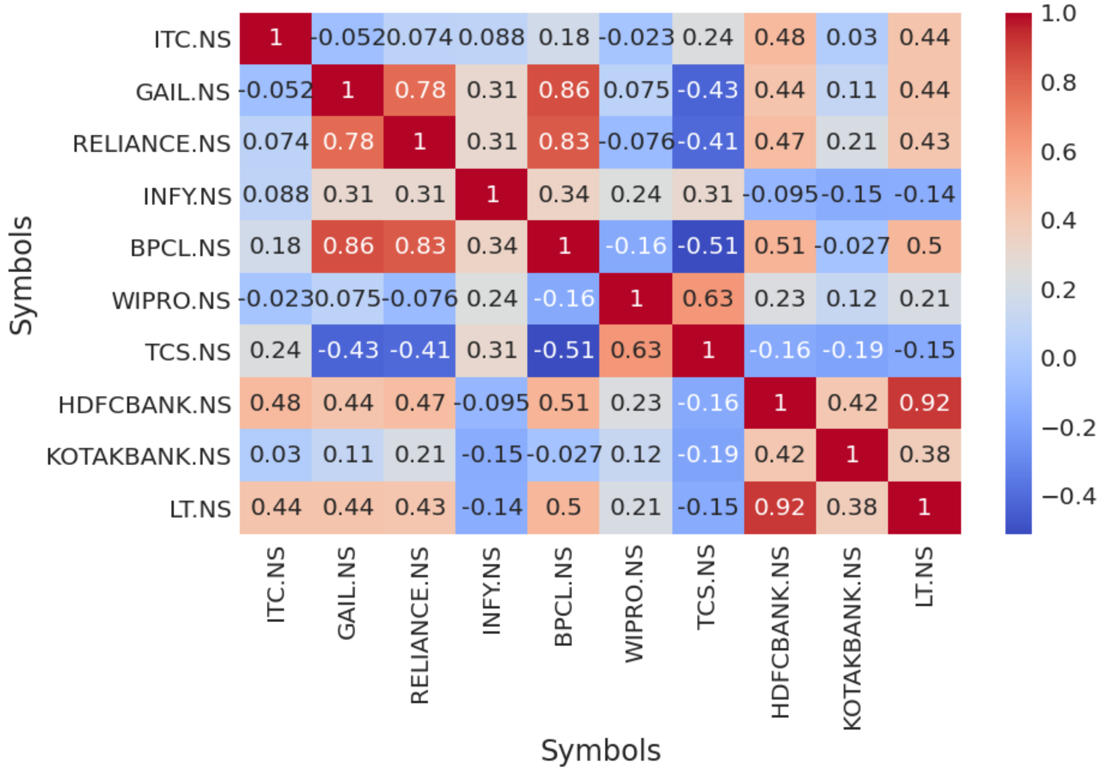
As you can see from the above plot, the stock with the least risk is TCS at around 0.38. But with portfolio optimisation, we can achieve even lower risk at 0.36, and still with a higher return than Google. And if we are willing to take slightly more risk at around the similar level of risk of TCS, we can achieve a much higher return of 0.30 with portfolio optimization.

reference: https://nbviewer.jupyter.org/github/tthustla/efficient_frontier/blob/master/Efficient%20_Frontier_in

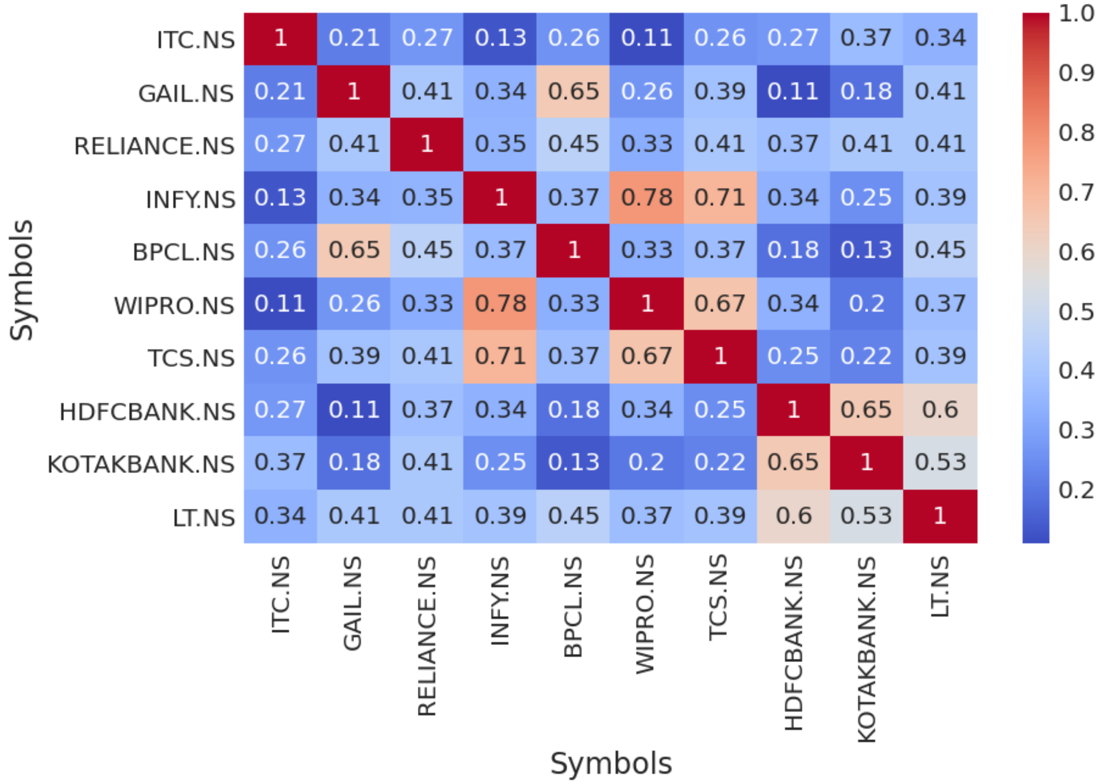
[35]:
```
from PortfolioOptimizer import *
```

[36]:
```
port = Portfolio(table)
```

[37]:
```
port.price_corr_map()
```




```
[38]: port.return_corr_map()
```

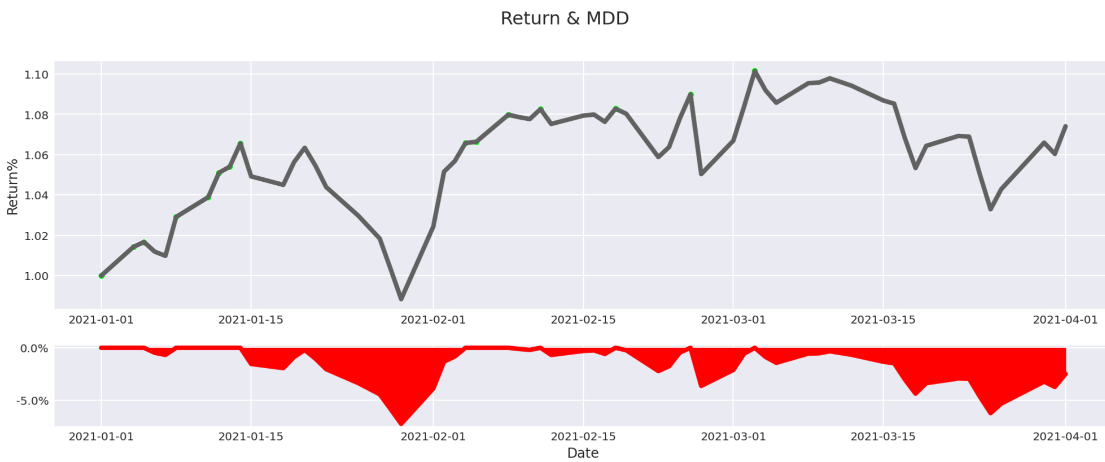


[39]:
```
port.Summary()
```

```
                           Period
From 2021-01-01  to 2021-04-01, 90 days.
------------------------------------------------------------
              Weights of Portfolio:
------------------------------------------------------------
ITC.NS                                       10.00%
GAIL.NS                                      10.00%
RELIANCE.NS                                  10.00%
INFY.NS                                      10.00%
BPCL.NS                                      10.00%
WIPRO.NS                                     10.00%
TCS.NS                                       10.00%
HDFCBANK.NS                                  10.00%
KOTAKBANK.NS                                 10.00%
LT.NS                                        10.00%
------------------------------------------------------------


               Technical Indicator:
------------------------------------------------------------
```

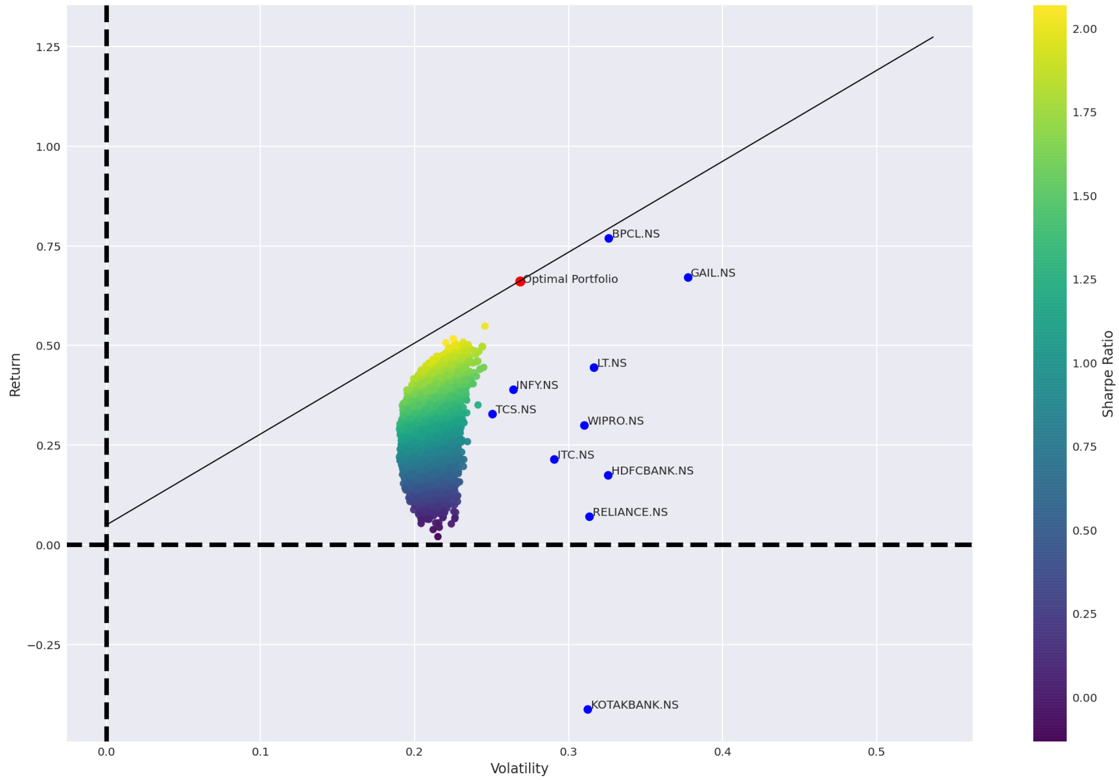
```
Average Return :                                                  0.295
Average Standard Deviation :                          0.201
Sharpe Ratio :                                                       1.222
Sotino Ratio :                                                        1.716
Maximum Drop Down :                                     0.073
------------------------------------------------------------
```

[40]:
```
port.Return_Plot()
```

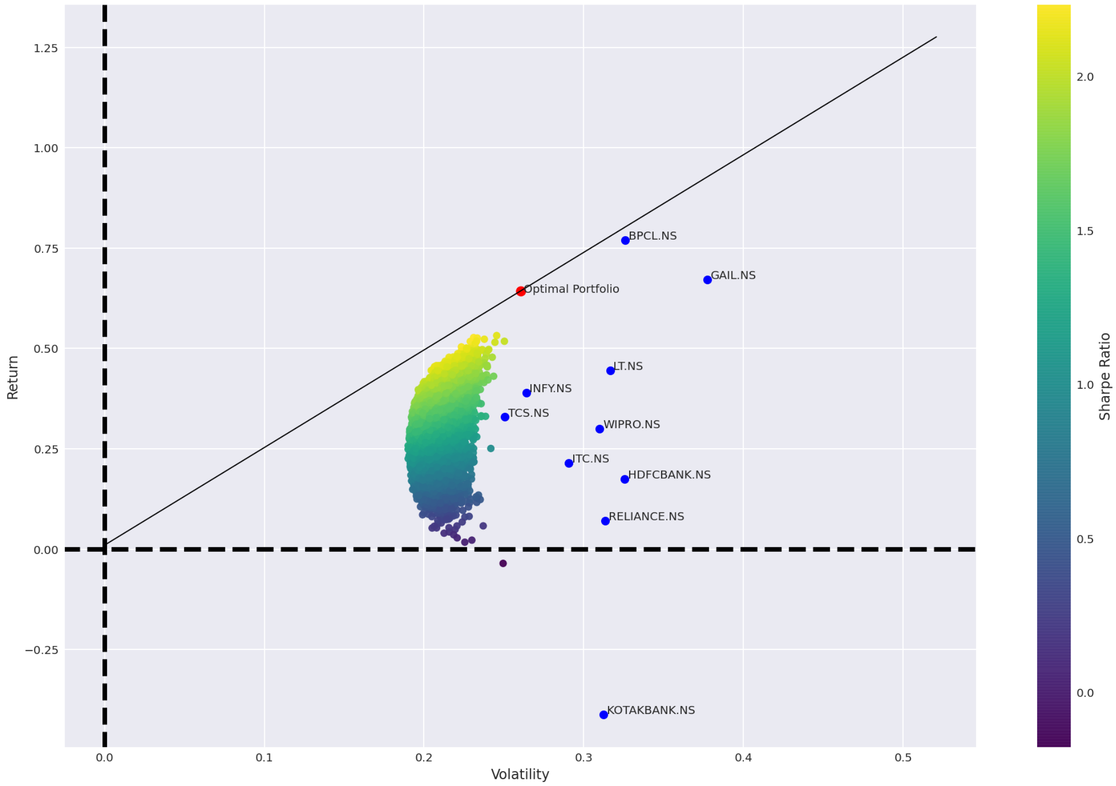


[41]:
```
port.set_optimize()
port.optimize_set()
port.Plot_Effcient_Frontier()
```

```
Begin :  2021-01-01 00:00:00
End :  2021-04-01 00:00:00
Rf :  0.05
```



[42]:
```python
# CML
port.set_optimize(rf=0.01)
port.Plot_Effcient_Frontier()
```



[43]:
```
port.Get_Best_Portfolio()
```

[43]:
```
(2.43125949103433,
 [0.011033830403874085,
  0.07752102975052605,
  8.383254485565261e-16,
  0.2392180975541218,
  0.6047691709285038,
  0.0,
  0.0,
  0.0,
  1.0836532951356836e-15,
  0.06745787136297333])
```

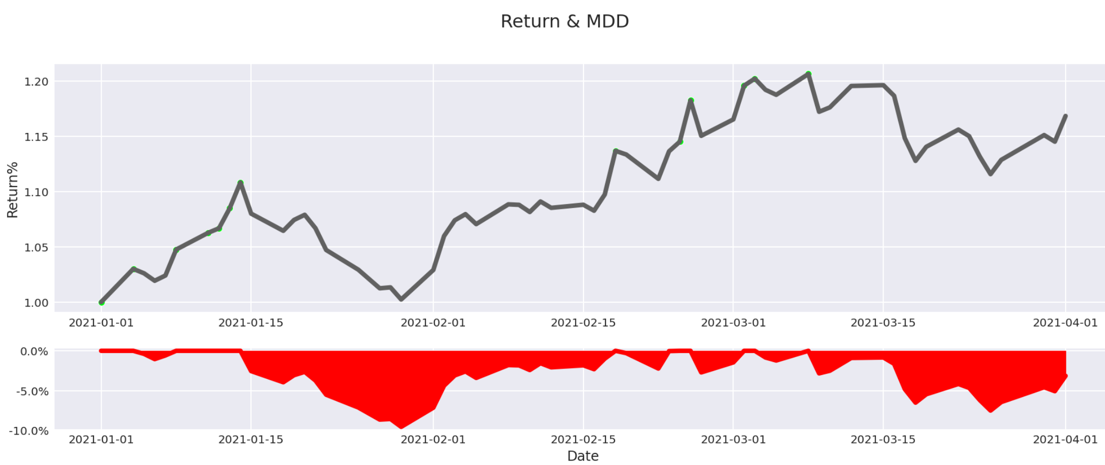
[44]:
```
port.set_weights(port.Get_Best_Portfolio()[1])
```

[45]:
```
port.Summary()
```

```
                              Period
From 2021-01-01  to 2021-04-01, 90 days.
------------------------------------------------------------
              Weights of Portfolio:
```

```
------------------------------------------------------------
ITC.NS                                        1.10%
GAIL.NS                                       7.75%
RELIANCE.NS                                   0.00%
INFY.NS                                      23.92%
BPCL.NS                                      60.48%
WIPRO.NS                                      0.00%
TCS.NS                                        0.00%
HDFCBANK.NS                                   0.00%
KOTAKBANK.NS                                  0.00%
LT.NS                                         6.75%
------------------------------------------------------------


               Technical Indicator:
------------------------------------------------------------
Average Return :                                                   0.643
Average Standard Deviation :                        0.260
Sharpe Ratio :                                                        2.278
Sotino Ratio :                                                         3.216
Maximum Drop Down :                                   0.096
------------------------------------------------------------
```

[46]:
```python
port.Return_Plot()
```

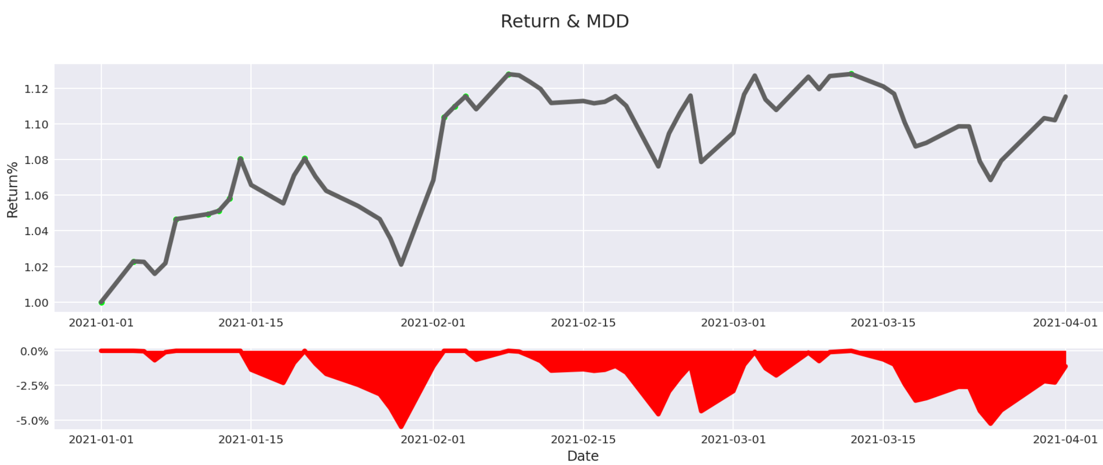


[47]:
```python
port.set_weights(port.Get_Best_Portfolio(method='mdd')[1])
port.Summary()
```

```
                      Period
From 2021-01-01  to 2021-04-01, 90 days.
------------------------------------------------------------
              Weights of Portfolio:
```

```
------------------------------------------------------------
ITC.NS                                        7.34%
GAIL.NS                                       0.00%
RELIANCE.NS                                   1.40%
INFY.NS                                       9.12%
BPCL.NS                                      18.72%
WIPRO.NS                                      0.00%
TCS.NS                                       24.19%
HDFCBANK.NS                                   0.00%
KOTAKBANK.NS                                  0.00%
LT.NS                                        39.23%
------------------------------------------------------------


               Technical Indicator:
------------------------------------------------------------
Average Return :                                                                   0.451
Average Standard Deviation :                                   0.221
Sharpe Ratio :                                                                        1.809
Sotino Ratio :                                                                         2.719
Maximum Drop Down :                                              0.055
------------------------------------------------------------
```

[48]:
```
port.Return_Plot()
```



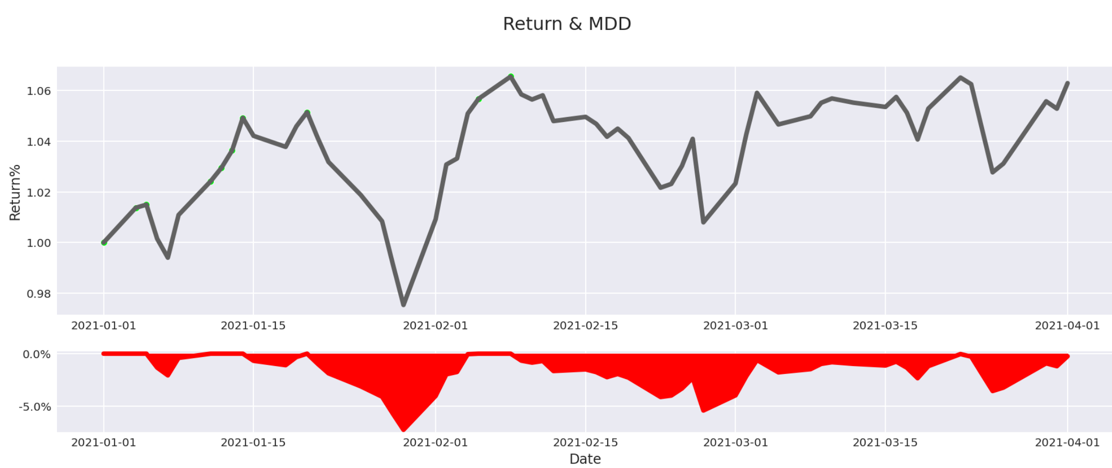
[49]:
```
# Volatility
port.set_weights(port.Get_Best_Portfolio(method='std')[1])
port.Summary()
```

```
                      Period
From 2021-01-01  to 2021-04-01, 90 days.
------------------------------------------------------------
```

```
               Weights of Portfolio:
------------------------------------------------------------
ITC.NS                                       23.44%
GAIL.NS                                       0.99%
RELIANCE.NS                                   4.65%
INFY.NS                                      19.80%
BPCL.NS                                      10.60%
WIPRO.NS                                      0.00%
TCS.NS                                       21.26%
HDFCBANK.NS                                   7.18%
KOTAKBANK.NS                                 12.08%
LT.NS                                         0.00%
------------------------------------------------------------


                Technical Indicator:
------------------------------------------------------------
Average Return :                                                     0.252
Average Standard Deviation :                              0.189
Sharpe Ratio :                                                          1.068
Sotino Ratio :                                                           1.535
Maximum Drop Down :                                         0.072
------------------------------------------------------------
```

[50]:

```
port.Return_Plot()
```



[51]:

```
table.head()
```

[51]:

```
Symbols         ITC.NS     GAIL.NS  …  KOTAKBANK.NS        LT.NS
Date                                …
2021-01-01  208.898636  119.134895  …   1994.050049  1297.000000
```

```
2021-01-04  208.459045  123.326057  …   1965.550049  1314.599976
2021-01-05  206.554199  124.578583  …   1959.750000  1306.300049
2021-01-06  200.644272  129.106964  …   1970.400024  1314.000000
2021-01-07  198.104477  128.577042  …   1952.400024  1338.949951

[5 rows x 10 columns]
```

[51]: