

## Problem 1

- **First Question (Python Approach):**

We use Python to download data for AMZN, NVDA, TSLA, and SPY from yfinance. Then we calculate  $\mu$  and  $\Sigma$ , resulting in the values shown below.

```
Mean daily returns ( $\mu$ ):  
Ticker  
AMZN    0.001594  
NVDA    0.003206  
TSLA    0.000728  
dtype: float64  
  
Covariance matrix ( $\Sigma$ ):  
Ticker      AMZN        NVDA        TSLA  
Ticker  
AMZN    0.000334  0.000241  0.000230  
NVDA    0.000241  0.001033  0.000316  
TSLA    0.000230  0.000316  0.001278
```

- **Calculating Weights (Zero Interest Rate):**

Using a zero interest rate, we apply the Analytical Solution formula and obtain the weights.

$$\omega^* = \frac{\Sigma^{-1}\mu}{\mathbf{1}^T \Sigma^{-1}\mu}$$

The solution is:

```
Optimal portfolio weights:  
AMZN: 0.6497  
NVDA: 0.4773  
TSLA: -0.1271
```

- **No Short-Selling Constraint:**

If we add a “No Short-Selling” constraint, we define our objective function to maximize the Sharpe Ratio and use `scipy.optimize.minimize` to perform the constrained optimization. We get:

```
Optimal portfolio weights (no short-selling):  
AMZN: 0.5572  
NVDA: 0.4428  
TSLA: 0.0000  
  
Optimal portfolio expected daily return: 0.0023  
Optimal portfolio daily volatility: 0.0206  
Optimal portfolio Sharpe Ratio: 0.1119
```

- **Perpare for Problem 2:**

We calculated  $\omega_{eq}$  in Python and added this row of data to MATLAB

```
wtsMarket = [0.344533; 0.193961; 0.461505];
```

## Problem 2

In this section, we use MATLAB to complete the following steps:

- **Data Prepare:**

First, we import the  $\mu$  and  $\Sigma$  obtained from Python into the code. We use SPY as the market portfolio to calculate the Sharpe ratio and the equilibrium risk premium  $\Pi$ .

- **Investor Views:**

#1 Absolute view: The expected annualized return of AMZN is greater than 0.005.

#2 Relative view: NVDA has an annualized return 0.002 higher than TSLA.

#3 Absolute view: The expected annualized return of TSLA is greater than 0.0012.

We use matrix  $P$  and vector  $q$  to define these absolute and relative views and use the  $\Omega$  matrix to represent the uncertainty of these views. The three omega values are set to 0.001, 0.02, and 0.05, indicating that we have more confidence in the first view.

- **Posterior Mean and Covariance of BL:**

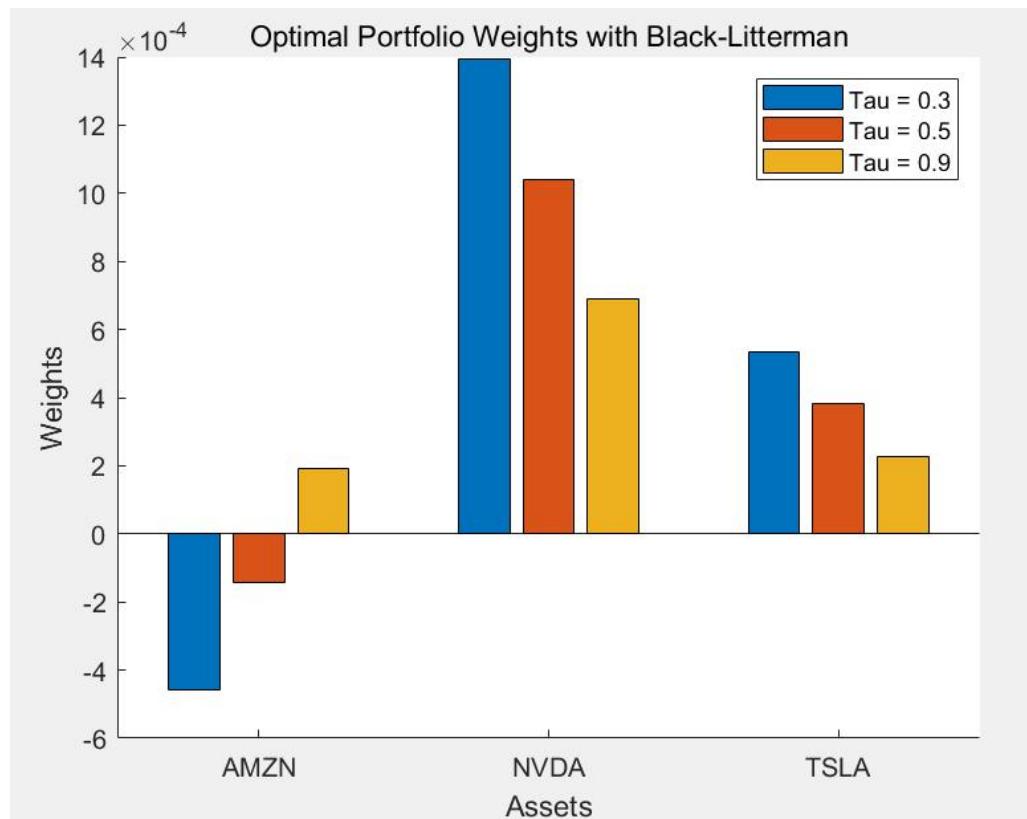
Using the investor views and the prior mean  $\Pi$ , we compute the adjusted mean  $M$  and covariance  $V$  under the Black-Litterman framework.

$$M = ((\tau\Sigma)^{-1} + P^T \Omega^{-1} P)^{-1} ((\tau\Sigma)^{-1} \Pi + P^T \Omega^{-1} q)$$

$$V = ((\tau\Sigma)^{-1} + P^T \Omega^{-1} P)^{-1}$$

- **Optimal Weights with Short-Selling:**

We calculate the optimal portfolio weights based on the analytical solution, which allows for short-selling.



- **Optimal Weights with No Short-Selling and Maximum Sharpe Ratio:**

Using quadprog and the Portfolio object in MATLAB, we add a non-negativity constraint to compute the optimal weights without allowing short-selling.

Asset_Name	Mean_Variance	BL_Tau_0.3	BL_Tau_0.5	BL_Tau_0.9
{'AMZN'}	0.56001	6.4503e-23	2.523e-12	0.17153
{'NVDA'}	0.43999	0.7335	0.7345	0.62341
{'TSLA'}	5.146e-12	0.2665	0.2655	0.20506

- **Visualization:**

The results show that as the  $\tau$  value increases, the portfolio weights under the Black-Litterman model gradually deviate from those of the mean-variance model. Specifically, the weight allocated to NVDA increases significantly, while the weight for AMZN decreases, indicating that investor views have a stronger impact at higher  $\tau$  values.

