High-dimensional Expected Utility Portfolios under the Spiked Covariance Model

4. Empirical analysis

4.2. Empirical process

4.2.1. Case 1

This research follows a systematic rolling window analysis pipeline. The specific steps are outlined below:

- **Step 1: Training Set Configuration**

  To investigate the impact of training set size, the sample size n is varied from 125 to 500 in increments of 25. For each n, historical data of the corresponding length immediately preceding the start of the test period is used as the training set.

- **Step 2: Parameter Optimization and Weight Calculation**

  For each training set size n:

  - The gradient descent method is used to optimize the parameters for the OEUP and GMVP strategies separately, obtaining Θ^*_{OEUP} and Θ^*_{GMVP}.
  - Based on the optimized parameters, portfolio weights are calculated for the proposed methods (SEM, SCME) and the three comparison methods (SDE, LSHE, NLSH).

- **Step 3: Out-of-Sample Performance Evaluation**

  A 30-day rolling window is applied within the test period:

  - Using the fixed portfolio weights obtained in Step 2, the out-of-sample return mean and variance are calculated for each window.
  - The corresponding **out-of-sample expected utility** is computed for each window according to the specified utility function.

- **Step 4: Statistical Analysis and Result Comparison**

  Steps 1 to 3 are independently repeated 500 times:

  - The mean and variance of the out-of-sample expected utility are calculated for each method and each training set size n.
  - The number (and proportion) of times the proposed methods achieve the highest expected utility among all five methods is recorded.
  - All statistical results are summarized in Table 2 for comprehensive comparative analysis.

The empirical results are summarized in Table 2, which reports the mean and variance (in parentheses) of the out-of-sample expected utility for different training sample sizes n.