

ChiNext-Based Iterative Refinement for No-Short-Sale Constrained MV Portfolios

Zixiao Tang

*School of Economics and Management, Southeast University, Nanjing, China
213221549@seu.edu.cn*

Abstract. Against the backdrop of increased volatility in global capital markets, the traditional mean-variance model faces challenges due to conflicts between its generation of negative weights and the institutional environment of China's A-share market, which imposes a no short-selling constraint. How to balance the return objectives with the no short-selling constraint has become an urgent issue to address. Moreover, the strong homogeneity and high volatility of the global emerging technology sector pose new tests to the applicability of the traditional mean-variance model. This study focuses on highly positively correlated stock portfolios on the ChiNext board and integrates an optimization approach that iteratively removes assets with negative weights: by gradually excluding negatively weighted assets and dynamically updating the covariance matrix, it solves for the efficient frontier under realistic constraints. The empirical analysis uses five years of monthly return data and finds that the optimized portfolio significantly concentrates on a small number of stocks with high Sharpe ratios, achieving fully positive weights when the target return is set above the market average; meanwhile, the strong sector linkage effect weakens the traditional diversification benefits, causing the portfolio to naturally tend toward concentrated holdings. This method provides a practical asset allocation approach for assets with strong sector linkages and holds practical significance for institutional investors seeking to balance returns and risks.

Keywords: Mean-variance model, Portfolio optimization, No short-selling constraint, Iterative removal, ChiNext board

1. Introduction

In today's context of heightened volatility in global capital markets and frequent occurrence of black swan events, how to strike a balance between high returns and high risks has become a common challenge faced by both institutional investors and individual wealth managers. The price co-movements among diversified assets such as stocks, bonds, and derivatives have become increasingly complex, and exposure to a single asset can easily result in substantial drawdowns. Portfolio management is no longer simply a matter of "not putting all eggs in one basket," but rather a refined science that requires quantitative trade-offs between returns and volatility. The mean-variance model, proposed by Harry Markowitz in 1952, serves as the cornerstone of modern portfolio theory and has been repeatedly validated and extended in response to this practical need.

However, the traditional mean-variance framework reveals many problems when confronted with real-world data and dynamic market structural changes. Revisiting and improving this model not only helps enhance the stability of asset allocation and reduce tail risks but also provides quantitative foundations for regulators to assess systemic risks and for fund managers to design products better aligned with investors' risk preferences. With the continuous expansion of long-term capital pools such as pensions and sovereign wealth funds, the optimization and innovation of portfolio theory are directly linked to the preservation and appreciation of billions of dollars as well as the efficiency of social wealth distribution. Therefore, ongoing research and refinement of the mean-variance model hold significant academic value and broad practical prospects.

This paper is structured as follows: The first section provides a literature review, systematically tracing the theoretical evolution of the Markowitz mean-variance model since 1952, with a focus on two main themes—expansion of constraint sets and iterative technical developments. The second section covers methodology, detailing the theoretical foundation, mathematical derivation, and solution process of the classical mean-variance model. The third section presents empirical results based on monthly data of 17 constituent stocks from the ChiNext board of China's A-share market, progressively applying the model and iteratively removing negatively weighted stocks to ultimately select portfolios that satisfy the no short-selling constraint and target returns, accompanied by detailed calculations and weight outcomes. The fourth section discusses the practical implications of the numerical results from perspectives such as sector linkage, target return settings, and negative weight handling. The fifth section concludes by summarizing the advantages of this study, acknowledging its limitations, and offering prospects for future research.

2. Literature review

The evolution of modern portfolio theory has always centered on the trade-off between returns and risks. The mean-variance framework proposed by Markowitz (1952) laid the foundation for modern portfolio theory. Zhou Yeqin et al. were among the first to conduct a localized validation of this framework within the institutional environment of China's A-share market, where short selling is restricted. Using weekly returns data of five stocks over three years, they demonstrated that even under short-selling prohibitions, the classical optimization model can still reduce risk and generate excess returns, thereby establishing "realistic constraints" as a common starting point for subsequent research [1].

Subsequently, Ning Tao used daily data of 30 domestic futures contracts over five years as a sample, embedding hierarchical clustering and risk parity into the mean-variance objective. The study found that the hierarchical clustering-based risk parity method significantly outperformed the mean-variance-based maximum Sharpe ratio approach in terms of in-sample and out-of-sample consistency, maximum drawdown, portfolio diversification, and risk-adjusted returns [2].

Two complementary studies that followed addressed high-dimensional asset contexts: Mynbayeva et al., using daily data of 1,000 stocks from CRSP between 1996 and 2017, proposed a sequentially rejective test procedure to solve the problem of estimation errors causing failures of the traditional Markowitz mean-variance portfolio in high dimensions. Their method achieved an approximately 50% improvement in out-of-sample Sharpe ratio and a 30% reduction in risk, significantly enhancing the practical performance of the classical mean-variance strategy [3]. Zhang Peng et al., using quarterly data of 20 A-share stocks, proposed a rotation algorithm with trading costs, borrowing constraints, and threshold constraints to solve a stochastic fuzzy mean-variance model. They demonstrated that the rotation algorithm can find optimal solutions for large-scale portfolio problems, validating the feasibility of a dimension-reduction and re-optimization approach

in large portfolios [4]. Together, these studies distilled a general paradigm: “High-dimensional assets → Clustering/Rotation-based dimension reduction → Mean-variance re-optimization → Realistic constraint sets,” which has been directly adopted by subsequent research.

In the domains of high-frequency and continuous-time modeling, Guo et al. proposed an Adaptive Online Moving Average Mean-Variance (AOLPIMV) algorithm that assumes weakly correlated return sequences and incorporates peer effects into return forecasting. Applied to daily data of 30 highly liquid stocks on the NYSE and NASDAQ from 2010 to 2020, the algorithm implements real-time rebalancing with transaction cost penalties, demonstrating significant outperformance compared to fixed-window and cost-ignoring benchmark mean-variance models [5]. Liu et al. solved a continuous-time mean-variance model with stochastic control that accounts for dynamically changing risk aversion based on wealth and volatility. Their empirical study on S&P 500 options from 1990 to 2018 shows that this strategy outperforms fixed-risk-aversion benchmarks in terms of Sharpe ratio and downside risk control [6]. Serban et al. introduced Tsallis entropy into the mean-variance framework to form a Mean-Variance-Entropy (MVE) model. Using daily returns of the top 20 cryptocurrencies on CoinMarketCap from 2018 to 2022, they found that although entropy regularization slightly reduces the Sharpe ratio, it substantially improves diversification [7].

In the Chinese market, Zhang Peng et al. further proposed a solution method based on conditional expectation mappings that incorporates transaction costs, borrowing constraints, and threshold constraints using quarterly data of 20 Shanghai Stock Exchange stocks. They concluded that final wealth is influenced by the risk trade-off parameter, and the optimal strategy involves holding high-risk assets while borrowing risk-free assets [8]. Xiong Wei et al., building upon these constraint sets, introduced an Adaptive Factor Coefficient Estimation (FACE) dynamic model to estimate the covariance matrix, addressing the imprecision of traditional mean-variance covariance estimation in high-dimensional and time-varying markets [9]. Their findings corroborate the robust return evidence obtained by Guo et al. (2023) in the U.S. market, jointly establishing a standardized procedure for the “high-dimensional robust estimation” module.

From the perspective of macroeconomic uncertainty, Huang et al. incorporated inflation risk into the mean-variance objective under a linear uncertainty distribution assumption. Numerical simulations showed that inflation uncertainty significantly reduces the weight of risky assets; weights increase with rising inflation mean but decrease as the distribution’s width expands, providing a template for future research to quantify non-financial macro factors as penalty terms [10].

Recent studies have further introduced ESG and financial contagion as new constraints. Shen et al. embedded contagion intensity via a Hawkes process into the mean-variance model. Using high-frequency data of 60 cross-industry U.S. stocks from 2008 to 2020, they found that strategies accounting for contagion risk achieved a 15% reduction in out-of-sample volatility and a 25% decrease in tail risk, significantly outperforming traditional mean-variance portfolios [11]. Varmaz et al. incorporated an ESG penalty term into the mean-variance objective, and empirical evidence from monthly data of 1,200 MSCI global stocks from 2012 to 2021 confirmed that under equal risk, the ESG-mean-variance strategy increased the Sharpe ratio by approximately 15% while effectively reducing carbon intensity [12].

In summary, recent research has advanced along two main lines: (1) the expansion of constraint sets from trading regulations such as short-selling restrictions, transaction costs, and borrowing thresholds to macroeconomic uncertainty like inflation and non-financial risks including ESG and contagion; (2) the evolution of technical pathways from static frameworks toward continuous-time models, complemented by iterative updates of high-dimensional robust estimation and dimension-

reduction algorithms. Together, these developments provide a systematic methodological evolution roadmap for reapplying mean-variance theory across global multi-asset, multi-institutional environments.

3. Methodology

The mean-variance model, proposed by Markowitz in 1952, is the cornerstone of modern portfolio theory. It uses the "mean" to represent the expected return of an asset or portfolio, and the "variance" to measure the uncertainty or risk of returns, assuming that investors seek to minimize risk for a given level of expected return. By calculating each asset's expected return, variance, and the covariance between assets, the model solves for the efficient frontier—a curve that is upward convex in the return-risk coordinate system, representing the set of optimal portfolios. The mean-variance model was the first to formalize returns and risks mathematically, laying a solid foundation for asset allocation and performance evaluation.

Among a series of portfolios with the same expected return, the portfolio with the minimum variance is defined as lying on the frontier boundary. Suppose there are n assets, and let w be an n -dimensional vector of portfolio weights. The solution for w is given by the following optimization problem:

$$\min_{\{w\}} \frac{1}{2} w^T V w \quad (1)$$

$$s.t. w^T e = E[\tilde{r}_p]$$

$$w^T 1 = 1$$

where e is the n -dimensional vector of expected returns for the n assets, V is the $n \times n$ variance-covariance matrix of asset returns, p is the expected return of the portfolio, and $E[\tilde{r}_p]$ is an n -dimensional vector of ones.

Construct the Lagrangian function:

$$\min_{\{w, \lambda, \gamma\}} L = \frac{1}{2} w^T V w + \lambda (E[\tilde{r}_p] - w^T e) + \gamma (1 - w^T 1) \quad (2)$$

Taking the partial derivative of w in equation (2), the expression for w_p can be obtained as follows:

$$w_p = \lambda(V^{-1}e) + \gamma(V^{-1}1) \quad (3)$$

From (2)(3), the portfolio weights can be expressed as:

$$\lambda = \frac{CE[\tilde{r}_p] - A}{D} \quad (4)$$

$$\gamma = \frac{B - AE[\tilde{r}_p]}{D} \quad (5)$$

Where,

$$A = \mathbf{1}^T \mathbf{V}^{-1} \mathbf{e} = \mathbf{e}^T \mathbf{V}^{-1} \mathbf{1} \quad (6)$$

$$B = \mathbf{e}^T \mathbf{V}^{-1} \mathbf{e} \quad (7)$$

$$C = \mathbf{1}^T \mathbf{V}^{-1} \mathbf{1} \quad (8)$$

$$D = BC - A^2 \quad (9)$$

Since the variance-covariance matrix $\mathbf{V}$ is positive definite, it follows that $B > 0$, $C > 0$. Considering that

$$(\mathbf{Ae} - B\mathbf{1})^T \mathbf{V}^{-1} (\mathbf{Ae} - B\mathbf{1}) = B(BC - A^2) \quad (10)$$

Due to the positive definiteness of $\mathbf{V}^{-1}$, $D > 0$.

Substituting equations (4) and (5) into equation (3), the unique portfolio weight vector $\mathbf{w}_p$ for the efficient frontier portfolio with expected return $E[\tilde{r}_p]$ can be obtained as follows:

$$\mathbf{w}_p = \mathbf{g} + \mathbf{h}E[\tilde{r}_p] \quad (11)$$

where

$$\mathbf{g} = \frac{1}{D} [B(\mathbf{V}^{-1}\mathbf{1}) - A(\mathbf{V}^{-1}\mathbf{e})] \quad (12)$$

$$\mathbf{h} = \frac{1}{D} [C(\mathbf{V}^{-1}\mathbf{e}) - A(\mathbf{V}^{-1}\mathbf{1})] \quad (13)$$

According to equation (11), $\mathbf{g}$ represents the portfolio weight vector on the efficient frontier corresponding to an expected return of zero, while $\mathbf{g} + \mathbf{h}$ corresponds to the portfolio weight vector with an expected return of one. The entire efficient frontier can be constructed as a linear combination of $\mathbf{g}$ and $\mathbf{g} + \mathbf{h}$.

4. Result

The original market data used in this study were obtained from the CSMAR database. The research objects are 17 constituent stocks of the ChiNext board in China's A-share market. The stock names and corresponding codes are as follows: 300002 Shenzhou Taiyue, 300007 Hanwei Technology, 300019 Guibao Technology, 300025 Huaxing Chuangye, 300042 Netac Technology, 300047 Tianyuan Dike, 300049 Furui Co., Ltd., 300051 Sanwu Internet, 300054 Dinglong Co., Ltd., 300065 Hailanxin, 300092 Kexin Electromechanical, 300101 Zhenxin Technology, 300139 Xiaocheng Technology, 300161 Huazhong CNC, 300169 Tiansheng New Material, 300181 Zuoli Pharmaceutical, and 300210 Senyuan Co., Ltd.

The data frequency for the 17 stocks is monthly, covering the period from January 2020 to December 2024, a total of 5 years or 60 calendar months. For each sample stock, the closing price on the first trading day of each month was taken as the representative value for that month.

For the monthly return data of the 17 stocks, the discrete return for each asset is calculated as follows: Let the price of asset i at time t be $P_{i,t}$, then the return series is defined by the price change between adjacent periods:

$$r_{i,t} = \frac{P_{i,t+1} - P_{i,t}}{P_{i,t}} \quad (14)$$

where $i = 1, 2, \dots, 17$ denotes the asset index and $t = 1, 2, \dots, 59$ denotes the time index. The 60 periods of original price data thus generate a return matrix of dimension 59×17 times.

Based on the return matrix, a 17-dimensional expected return vector e is constructed, where each element e_i corresponds to the sample mean return of asset i , calculated as the arithmetic average:

$$e_i = \frac{1}{59} \sum_{t=1}^{59} r_{i,t} \quad (15)$$

This vector characterizes the expected return profile of the portfolio, denoted as $\mathbf{e} = [e_1, e_2, \dots, e_{17}]^T$.

Further, the variance-covariance matrix V is calculated to quantify the risk structure. Its elements σ_{ij} are given by:

$$\sigma_{ij} = \frac{1}{58} \sum_{t=1}^{59} (r_{i,t} - e_i)(r_{j,t} - e_j) \quad (16)$$

The diagonal elements of matrix V represent the sample variances of each asset's returns, while the off-diagonal elements characterize the linear co-movement of returns between assets. It was found that all elements of V are positive.

The first iteration is then conducted. Substituting the e and V data of the 17 stocks into equations (6), (7), and (8) yields $A = 3.65$, $B = 0.19$, and $C = 123.31$. Substituting these values into equation (9) gives $D = 9.80$. Based on formulas (12) and (13), the corresponding g and h vectors for the assets are computed.

For different target returns $E[\tilde{r}]$ in the interval $[0, 0.06]$, the points corresponding to the minimum standard deviation σ are selected. Connecting these points forms the efficient frontier curve, as shown in Figure 1.

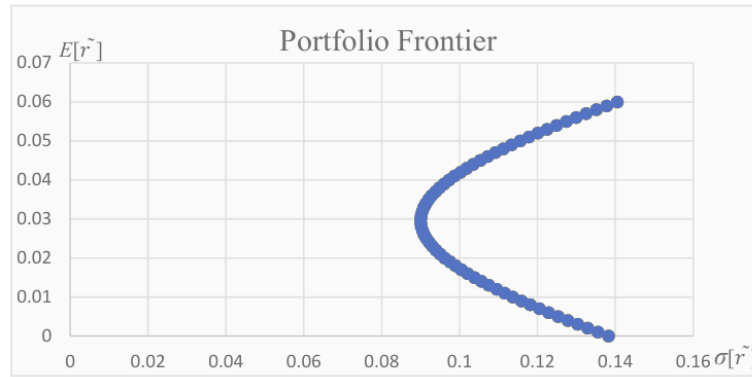


Figure 1. Portfolio efficient frontier

Considering that the current market average return is $\frac{A}{C} = 2.96\%$, a target return of 0.04 can be chosen for calculating the efficient frontier solution. By substituting $E[\tilde{r}_p] = 0.04$ into equation (11), the asset weights w at this target return are obtained, as shown in Table 1.

Table 1. Portfolio weights of 17 stocks in the first iteration

Stock Code	w
300002	27.34%
300007	-8.13%
300019	24.37%
300025	3.04%
300042	-25.66%
300047	-49.35%
300049	21.01%
300051	17.50%
300054	19.95%
300065	-11.40%
300092	-12.49%
300101	-4.96%
300139	23.91%
300161	14.39%
300169	-3.86%
300181	30.31%
300210	34.03%

Based on the current results, due to the practical restriction of no short selling in stocks, the seven stocks with negative weights $w < 0$ that performed relatively poorly in this iteration—300007 Hanwei Technology, 300042 Netac Technology, 300047 Tianyuan Dike, 300065 Hailanxin, 300092 Kexin Electromechanical, 300101 Zhenxin Technology, and 300169 Tiansheng New Material—are excluded from the portfolio by adopting a “no negative weight” policy, meaning these stocks are directly removed and not invested in.

After incorporating the constraint of excluding these seven stocks, a second iteration is conducted. Substituting the e and V data of the remaining 10 stocks into equations (6,7,8) yields $A = 2.66$, $B = 0.10$, and $C = 98.23$. Substituting these values into equation (9) gives $D = 2.78$. Based on formulas (12,13), the corresponding g and h vectors are calculated. Considering that $\frac{A}{C} = 2.71\%$ at this stage, a target return of 0.04 can continue to be used for calculating the efficient frontier solution. By substituting $E[\tilde{r}_p] = 0.04$ into equation (11), the asset weights w at this target return are obtained, as shown in Table 2.

Table 2. Portfolio weights of 17 stocks in the second iteration

Stock Code	w
300002	25.51%
300007	0
300019	0.03%
300025	12.01%
300042	0
300047	0
300049	35.29%
300051	-4.03%
300054	16.37%
300065	0
300092	0
300101	0
300139	-23.16%
300161	-13.85%
300169	0
300181	27.12%
300210	24.70%

Based on the results of the new iteration and considering the no-short-selling constraint in real trading, we continue to apply the principle of excluding negative weights. Therefore, the three stocks that performed relatively poorly this round—300051 Sanwu Internet, 300139 Xiaocheng Technology, and 300161 Huazhong CNC—are also directly removed and excluded from subsequent portfolio construction.

After excluding these three stocks in the second round, a third iteration is performed with the remaining seven assets. The parameters are re-estimated, yielding $A=2.707, B=0.0957, C=87.482, D=1.046$. Since $\frac{A}{C}=3.09\%$ is still below the acceptable threshold from the previous round, the target expected return $E[\tilde{r}_p]$ remains at 0.04. Substituting this return into equation (11) produces the portfolio weights for the third iteration, as shown in Table 3.

Table 3. Portfolio weights of 17 stocks in the third iteration

Stock Code	w
300002	25.26%
300007	0
300019	-14.23%
300025	8.45%
300042	0
300047	0
300049	48.37%
300051	0
300054	2.04%
300065	0
300092	0
300101	0
300139	0
300161	0
300169	0
300181	8.28%
300210	21.82%

Given the inability to short sell in actual trading, we continue the approach of “retaining only the strong and discarding the weak”. Therefore, the stock 300019 Guibao Technology, which shows a negative weight in this round, is removed and excluded from subsequent portfolio considerations.

In the fourth iteration, excluding all previously removed stocks, the parameters are re-estimated using the remaining 6 securities. Substituting e and V into equations (6), (7), and (8) yields $A = 2.7101$, $B = 0.0957$, and $C = 85.28$; subsequently, from equation (9), $D = 0.8194$. Considering $\frac{A}{C} = 3.18\%$, the target return remains at 0.04. By substituting $E[\tilde{r}_p] = 0.04$ into equation (11), the updated portfolio weights w are obtained, as shown in Table 4.

Table 4. Portfolio weights of 17 stocks in the fourth iteration

Stock Code	w
300002	26.72%
300007	0
300019	0
300025	4.53%
300042	0
300047	0
300049	54.17%
300051	0
300054	-11.65%
300065	0
300092	0
300101	0
300139	0
300161	0
300169	0
300181	4.06%
300210	22.17%

Similarly, stock 300054 Dinglong Co., Ltd. is excluded from subsequent portfolio construction.

After removing Dinglong Co., Ltd., the fifth iteration is performed. Since $\frac{A}{C}=3.40\%$ still satisfies the threshold, the same target return $E[\tilde{r}_p]=0.04$ is used. The portfolio weights for the remaining assets are shown in Table 5.

Table 5. Portfolio weights of 17 stocks in the fifth iteration

Stock Code	w
300002	26.19%
300007	0
300019	0
300025	2.13%
300042	0
300047	0
300049	57.67%
300051	0
300054	0
300065	0
300092	0
300101	0
300139	0
300161	0
300169	0
300181	-6.49%
300210	20.50%

At this stage, stock 300181 Zuoli Pharmaceutical has a negative weight and is therefore removed.

The sixth iteration excludes Zuoli Pharmaceutical. With the remaining assets, since $\frac{A}{C}=3.73\%$ still meets the criteria, the target return remains $E[\tilde{r}_p]=0.04$. The corresponding portfolio weights are listed in Table 6.

Table 6. Portfolio weights of 17 stocks in the sixth iteration

Stock Code	w
300002	23.18%
300007	0
300019	0
300025	-2.87%
300042	0
300047	0
300049	61.34%
300051	0
300054	0
300065	0
300092	0
300101	0
300139	0
300161	0
300169	0
300181	0
300210	18.35%

Similarly, stock 300025 Huaxing Chuangye is removed, and portfolio weights are reallocated among the remaining three stocks.

In the seventh iteration, after re-estimating e and V for the three remaining securities, we obtain $A = 2.2422, B = 0.0872, C = 58.45$, and $D = 0.0682$. Given that the market average return $\frac{A}{C} = 3.84\%$ still supports a 4% return target, the same $E[\tilde{r}_p] = 0.04$ is used to solve equation (11). The updated portfolio weights are shown in Table 7.

Table 7. Portfolio weights of 17 stocks in the seventh iteration

Stock Code	w
300002	20.04%
300007	0
300019	0
300025	0
300042	0
300047	0
300049	62.91%
300051	0
300054	0
300065	0
300092	0
300101	0
300139	0
300161	0
300169	0
300181	0
300210	17.05%

As shown in Table 7, after the seventh iteration, only three stocks—300002 Shenzhou Taiyue, 300049 Furui Co., Ltd., and 300210 Senyuan Co., Ltd.—retain positive weights, with weights of 20.04%, 62.91%, and 17.05%, respectively. All these weights lie strictly within the interval (0, 1). The weights of the other 14 stocks have been reduced to zero, indicating that after seven rounds of screening, the portfolio has become highly concentrated in these three best-performing securities, while simultaneously satisfying the constraints of no short selling and a 4% target return.

5. Discussion

From the final portfolio weights, after seven rounds of iterative removal of negative weights, the original 17 ChiNext constituent stocks were compressed to just three stocks: 300002 Shenzhou Taiyue, 300049 Furui Co., Ltd., and 300210 Senyuan Co., Ltd., resulting in a relatively high concentration, with the stock 300049 Furui Co., Ltd.—which has the highest sample mean return—accounting for more than half of the portfolio weight. This high concentration intuitively reflects the mean-variance optimization’s tendency, under a “no short selling” constraint, to select assets with high Sharpe ratios. On a practical level, these results suggest that when return correlations among investment targets are strong and short selling is strictly prohibited, the traditional mean-variance model naturally tends toward a “winner-takes-all” style of concentrated holdings. This phenomenon is especially evident in small-to-mid cap, high-volatility sectors with highly consistent risk factors.

This study selects 17 ChiNext constituent stocks from China’s A-share market as the sample to fix the trading system and regulatory environment, so that weight differences reflect only individual stock risk-return characteristics. The time window chosen is monthly data from January 2020 to December 2024. On one hand, the relatively long period reduces the impact of short-term economic

fluctuations; on the other hand, monthly frequency balances signal-to-noise ratio effectively when estimating covariance, suppressing noise present in daily data while retaining a sufficient sample size ($n=60$) to satisfy the law of large numbers.

It is noteworthy that the 17 stocks exhibit significant sectoral co-movement during the sample period—all elements of the sample covariance matrix are positive, significantly higher than similar-sized portfolios on the main board, indicating strong positive correlation within the ChiNext board driven by common factors such as policy expectations for scientific and technological innovation. This high positive correlation weakens the traditional diversification benefits and further amplifies the concentration effect caused by the iterative exclusion of negative weights.

The initial target expected return of 4% was chosen primarily to rigidly exceed the “market benchmark return”: across all seven iterations, the market average return $\frac{A}{C}$ ranged consistently between 2.96% and 3.84%, significantly below 4%, thereby ensuring the portfolio theoretically offers a risk-adjusted return higher than the market average, satisfying investors’ basic goal to outperform the market. If the target return is further raised to 5%, the optimization under the no-short-selling constraint quickly converges to a single stock—300049 Furui Co., Ltd.—with a weight approaching 100%. This phenomenon stems from the “co-movement” effect caused by the generally positive covariance matrix within the ChiNext board: as the expected return target increases, the return weight is amplified and the relative importance of risk weight is compressed, making it difficult to hedge risk effectively through diversification in an environment where asset covariances are mostly positive. Excessively high return targets exacerbate this contradiction, ultimately causing the optimal portfolio to concentrate nearly all weights in the single stock with the highest expected return. Therefore, the 4% target strikes a balance, leaving enough room for diversification within the feasible region while avoiding the “winner-takes-all” collapse caused by overly ambitious return goals.

Regarding the treatment of negative weights, this study adopts a direct exclusion iterative approach, which has the advantages of computational simplicity, intuitive interpretability, and alignment with practical brokerage system restrictions prohibiting short selling in China [13].

In terms of industry distribution, the final three selected stocks belong to software services (300002 Shenzhou Taiyue), pharmaceuticals and biotechnology (300049 Furui Co., Ltd.), and specialized equipment (300210 Senyuan Co., Ltd.). Although all are from the ChiNext board, the considerable differences in sub-sector imply that the mean-variance model can still identify low-correlation sub-industries within a sector, partially offsetting the diversification failure caused by high homogeneity.

6. Conclusion

Based on the traditional Markowitz mean-variance framework and considering the no-short-selling constraint in China’s A-share ChiNext market, this study employs monthly market data from 2020 to 2024 and uses an iterative optimization approach that removes negative weights in seven rounds. The final result is an optimal portfolio of three stocks with strictly positive weights meeting a 4% target return. This process not only verifies the adaptability of the mean-variance model under the local institutional environment but also provides a replicable asset allocation paradigm for small-to-mid cap, high-volatility sectors and assets with strong sectoral co-movement.

Despite validating the effectiveness of the iterative optimization path under the no-short-selling constraint, this study has several limitations: First, the sample focuses on 17 positively correlated stocks in the ChiNext board, so the conclusions are most applicable to sectors with mutualistic

characteristics; their generalizability to industries with divergent asset performance or strong competitive or adversarial dynamics remains to be tested. Second, when expanding to the entire A-share market with a larger asset universe, the computational complexity of estimating the covariance matrix increases substantially. Third, although the iterative exclusion method complies with the no-short-selling constraint and is easy to implement, its binary nature (“include or exclude”) may lead to loss of suboptimal assets that still have diversification potential.

To address these limitations, future research could extend the analysis to markets with different structural characteristics to test universality, develop more efficient algorithms combined with factor models to handle large-scale computation challenges, and explore multi-constraint models incorporating emerging factors such as ESG. These directions hold promise for enhancing the model’s applicability in complex real-world environments.

References

- [1] Zhou, Y. Q., Wu, D., Huang, L., Wang, Y. C., & Zhou, Z. D. (2019). Innovation and application of modern portfolio theory in the Chinese market. *Financial Education Research*, 32(06), 34–39.
- [2] Ning, T. (2022). Portfolio optimization research based on hierarchical clustering. *Statistics and Decision*, 38(06), 180–184.
- [3] Mynbayeva, E., Lamb, J. D., & Zhao, Y. (2022). Why estimation alone causes Markowitz portfolio selection to fail and what we might do about it. *European Journal of Operational Research*, 301(2), 694–707.
- [4] Zhang, P., Li, L. X., Li, J. X., & Zeng, Y. Q. (2023). Stochastic fuzzy mean-variance portfolio optimization based on rotation algorithm. *Operations Research and Management*, 32(05), 42–48.
- [5] Guo, S., Gu, J.-W., Ching, W.-K., & Lyu, B. (2023). Adaptive online mean-variance portfolio selection with transaction costs. *Quantitative Finance*, 24(1), 59–82.
- [6] Liu, S. (2024). Mean-variance portfolio with wealth and volatility dependent risk aversion. *Quantitative Finance*, 24(6), 735–751.
- [7] Serban, F., & Vrinceanu, B.-P. (2025). Mean-Variance-Entropy Framework for Cryptocurrency Portfolio Optimization. *Mathematics*, 13(10), 1693.
- [8] Zhang, P., Li, J. X., Cui, S. L., & Zeng, Y. Q. (2024). Time-consistent multi-stage mean-variance portfolio strategy with practical constraints. *Operations Research and Management*, 33(01), 205–211.
- [9] Xiong, W., Shen, T., & Tang, X. B. (2025). Application of robust dual mean-variance management in portfolio construction. *Journal of Mathematical Statistics and Management*, 44(01), 55–69.
- [10] Huang, X., Ma, D., & Choe, K.-I. (2023). Uncertain mean-variance portfolio model with inflation taking linear uncertainty distributions. *International Review of Economics & Finance*, 87, 203–217.
- [11] Shen, Y., & Zou, B. (2022). Mean-variance portfolio selection in contagious markets. *SIAM Journal on Financial Mathematics*, 13(2), 391–425.
- [12] Varmaz, A., Fieberg, C., & Poddig, T. (2024). Portfolio optimization for sustainable investments. *Annals of Operations Research*, 341(2-3), 1151–1176.
- [13] Fu, Y. H., Ng, K. M., Huang, B., & Huang, H. C. (2015). Portfolio optimization with transaction costs: A two-period mean-variance model. *Annals of Operations Research*, 233(1), 135–156.