Application of Mean-variance Model of 11 Industries in Chinese A Share Market

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Abstract. The Markowitz mean-variance model is served to find a balance between stock returns and risks. Gains in the stock markets of this economic powerhouse, especially the A-share market, are remarkable. In this paper, stocks of 11 leading enterprises from 11 industries such as manufacturing, finance, energy, etc. in China's A-share market are selected. The mean-variance model contributes to calculate the weight of each stock and construct a minimum variance portfolio. By comparing the minimum variance portfolio with an equal-weighted portfolio and the market portfolio (represented by the Shanghai Composite Index), it is found that the minimum variance portfolio outperforms the market portfolio. The robustness test by removing the two largest and smallest stocks in the portfolio still holds. This study provides a feasible method to diversify the risk of the asset portfolio and improve the return and provides an important reference for related investors' portfolio construction behavior in the A-share market.

Keywords: Mean-variance model, Monte-Carlo simulation, portfolio formation.

1. Introduction

Since China acceded to the WTO in 2001, China's economy has continued to develop, and the influence of the stock market in the world has increased day by day. Over the past two decades, the number of listed companies in China's stock market has been increasing, and the outstanding market capitalization has increased by 6.5 times, ranking second in the world after the United States. The SSE Composite Index is the most important stock index in China's stock market, with ups and downs affecting investor sentiment and market confidence and is widely used in market research and portfolio construction. In recent years, geopolitics has brought greater uncertainty to the Chinese stock market, making it particularly important to find portfolios that can outperform the market portfolio.

The mean-variance model proposed by Markowitz provides a theoretical cornerstone for modern portfolio construction [1]. Since then, scholars have explored the generalizability of the model based on its characteristics. Radović et al. studied the Serbian stock market, which is illiquid, has a low liquid market capitalization, and has a small number of outstanding shares, and found that it is not possible to diversify by industry and that the Markowitz model, which applies to highly liquid and diversified stocks, is not applicable [2]. Lee et al. studied the application of Markowitz to the Malaysian stock market and found that it does not apply to the Malaysian stock market. the feasibility of applying the Markowitz model to diversify systematic risk in the Malaysian stock market and found that the model is well applicable and can help build investor confidence in investment decisions [3]. In addition, Zaimovic used Principal Component Analysis (PCA) to study asset selection in southeastern European stock markets and found that an analytical approach combining PCA components with market portfolio effectiveness boundaries can simplify the asset selection process in southeastern European stocks [4]. Other scholars made a comparison between the mean-variance model and other models. Simaan mentioned the mean-variance model and the mean-absolute deviation model to make a comparison, and found that the mean-absolute deviation model has larger error among investors with higher risk tolerance [5]. Alexander linked the value-at-risk with the mean-variance model to study the effect of jointly using the two methods to construct portfolios and found that value-at-risk (VaR) does not provide better results [6]. Hakansson mentioned the mean-variance model and the capital growth model and made a comparison, and found that the capital growth model is not as good as the former in portfolio selection [7]. Therefore, Markowitz's mean-variance model is more effective for asset portfolio construction.

However, most of the existing studies on Chinese stock market portfolios focus on specific industries, and there are fewer cross-industry studies. Jiang applies principal component analysis to stocks in the carbon trading sector, selects four stocks, and finds that the Markowitz model has certain applicability and feasibility for Chinese carbon trading stocks [8]. Zeng selects stocks in the pharmaceutical industry to conduct a Fama-French three-factor empirical analysis, and finds that the pharmaceutical industry has low risk and certain defensive properties [9]. Zeng selects stocks in the new energy and precious metal sectors to construct a portfolio, compares it with the market index, and finds that the constructed portfolio outperforms the market portfolio [10]. In summary, the research on relevant cross-industry portfolios is still limited, which makes this study important for portfolio application in the A-share market.

The remainder of the paper is organized as follows. Section 2 is about the sources of data and summary statistics. Section 3 describes the methods. Section 4 shows the weights and performance of each asset in the portfolio and compares it with the market index for the robustness test. Section 5 summarizes.

2. Data

2.1. Data

The data used to construct the portfolio is from the China Stock Market & Accounting Research Database (CSMAR), and the market portfolio data (Shanghai(securities)composite index, SSE Composite Index) comes from Choice Financial Terminal. Since the SSE Composite Index covers listed stocks in various industries, this paper selects 11 stocks in 11 industries closely related to national production and life: manufacturing, finance, energy, information technology, major consumption, optional consumption, raw materials, medicine and health, communication services, utilities and real estate, and selects 1 leading stock in each of these industries considering the indicators of market capitalization under circulation, popularity and trading volume. Table 1 shows the stock codes and corresponding company names of the stocks selected in this paper.

Table 1. Selected Stocks

Stock Code	Company
600028	China Petrochemical Corporation
600048	Poly Development Holding Group Co. Ltd.
600050	China United Telecommunications Co. Ltd.
600111	China Northern Rare Earth (Group) High-Tech Co. Ltd.
600519	Kweichow moutai Co.Ltd.
600887	Inner Mongolia Yili Industrial Group Co. Ltd.
600905	China Three Gorges Renewables(Group)Co. Ltd.
601669	Power Construction Corporation of China, Ltd.
601988	Bank of China Limited
603259	WuXi AppTec
688111	Beijing Kingsoft Office Software, Inc.

A total of 486 observations from June 10, 2021 - June 9, 2023, are selected to calculate the weight of assets in the portfolio. Finally, the expected return of the portfolio is calculated for a total of 162 observations from June 10, 2023-February 5, 2024, and compared with the market portfolio (represented by the SSE Composite Index) in this period.

2.2. Summary Statistics

In this paper, this paper first selects the closing prices of 11 stocks without considering dividends from June 10, 2021, to February 5, 2024, to calculate the return $r_{i,t}$ and get 648 observations with the following formula:

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

Where $r_{i,t}$ is the return of stock i on day t, $P_{i,t}$ is the closing price of stock i on day t without considering dividends, and $P_{i,t-1}$ is the closing price of stock i on day t-1 without considering dividends. Summary statistics for the 11 stocks are shown in Table 2.

Table 2. Summary Statistics

Stock Code	Mean	Max	Min	Std Dev	Cumulative Return
600028	0.05	7.87	-6.42	0.015	-10.07
600048	-0.02	10.01	-9.98	0.025	-33.54
600050	0.02	10.11	-9.59	0.030	-14.8
600111	-0.00	10.00	-10.01	0.017	-39.18
600519	-0.03	9.50	-7.57	0.016	-0.73
600887	-0.04	6.38	-10.01	0.028	6.68
600905	0.12	44.15	-8.39	0.027	-20.38
601669	0.07	10.07	-10.04	0.011	-16.97
601988	0.06	10.05	-7.12	0.029	8.43
603259	-0.13	10.00	-10.01	0.036	-27.82
688111	-0.04	18,69	-17.73	0.066	-77.37

Note: Mean, Max, Min, and cumulative returns are displayed in percentage terms.

From the table above, 601669 has the highest average return and 603259 has the lowest average return. 688111 has the lowest cumulative return, the lowest single-day return, and the most volatile return. 601988 has the highest cumulative return. 600905 has the highest single-day return.

3. Methodology

3.1. Monte Carlo Simulation

The Monte Carlo model is a computational method to obtain an approximate solution through numerical simulation experiments, based on the probabilistic statistical theory approach, which relates the problem to be solved to the probabilistic model and implements statistical simulation and sampling with the help of a computer. Specifically, the paper first generates random weights with the help of a computer such that the weights of each asset are greater than 0 and the sum of the weights is 1. Subsequently, portfolio return and expected risk (volatility, variance) under these weights are calculated using the generated random weights and the expected returns of the 11 stocks. The experiment is then repeated for 750,000 repetitions and this is plotted to obtain the effectiveness bounds for the asset portfolio.

3.2. Mean-Variance Model

Markowitz proposed the mean-variance model in 1952. The main ideas are at the beginning of the period to decide the type of securities, choose the optimal asset portfolio for investment, so that the same risk when the rate of return is as high as possible, or the same return when the risk is as small as possible, to achieve a balance in the return and risk. Suppose there are n kinds of assets in the market, in which the return is $r_1, r_2, \cdots, r_n$, and the weight is $\omega_1, \omega_2, \cdots, \omega_n$, which satisfies $\sum_{i=1}^{n} \omega_i = 1$. The expected return of the portfolio is:

$$E(r_p) = \sum_{i=1}^{n} \omega_i E(r_i) \tag{2}$$

Using the volatility of a stock as a proxy for stock risk, the risk of the portfolio is

$$Var(r_p) = \sum_{i=1}^{n} \omega_i^2 \, Var(r_i) + \sum_{i \neq j} \omega_i \, \omega_j Cov(r_i, r_j) \tag{3}$$

Where $Var(r_i)$ is the variance of returns and $Cov(r_i, r_j)$ is the covariance of stock i and stock j returns.

4. Results

4.1. Results of Portfolios

First, based on a total of 486 observations from June 10, 2021, to June 9, 2023, 750,000 repetitions of the experiment were conducted through Monte Carlo simulation, and the mean-variance image was obtained as shown in the following Fig. 1. The upper-leftmost curve is the validity boundary.

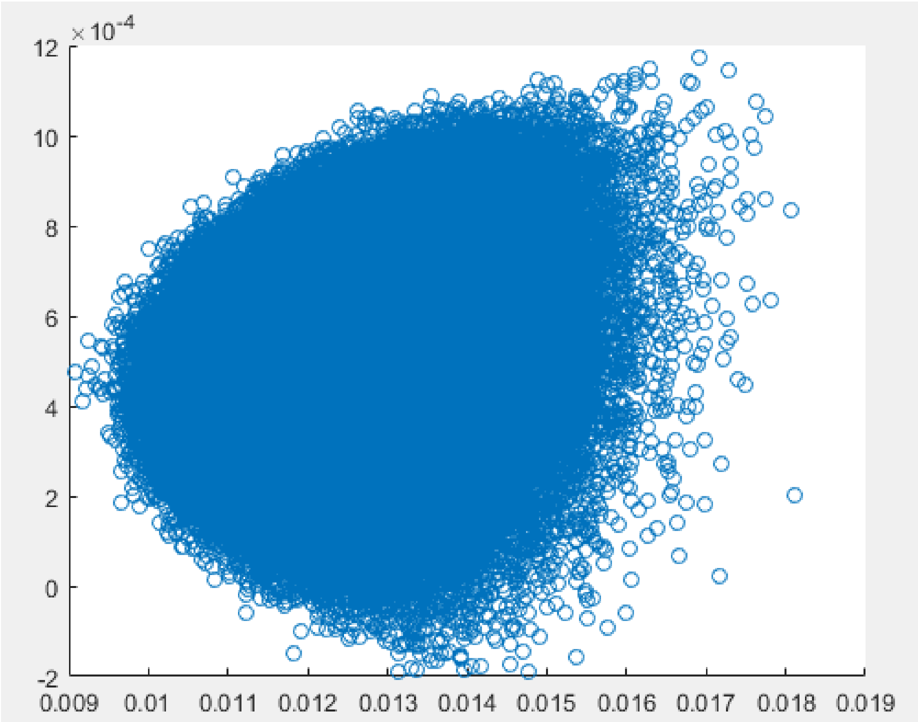

Figure 1. Monte-Carlo simulation

The optimal weights of the minimum variance model obtained from the above process are shown below in Table 3:

Table 3. Results of Minimum Variance Models

Stock Code	Weight
600028	0.2285
600048	0.0564
600050	0.0142
600111	0.0733
600519	0.0242
600887	0.1839
600905	0.0292
601669	0.0043
601988	0.3513
603259	0.0207
688111	0.0139

In the minimum variance portfolio, the weight of each asset varies. 601988, 600028, and 600887 occupy a larger share of the portfolio, 35.13%, 22.85%, and 18.39%, respectively; while 601669, 600050, and 688111 occupy a smaller share, 0.43%, 1.42%, and 1.39%, respectively. In addition, the minimum variance model expected return obtained based on the in-sample data is 0.05% and the risk is 0.01%.

Subsequently, based on the calculated weights of each asset and stock return in the coming period, asset portfolio return is calculated and compared with the return of the SSE Composite Index over the same period (See Fig. 2). The constructed portfolio is compared with the market portfolio. The constructed portfolio consists of a minimum variance portfolio and an equal-weighted portfolio. The following chart demonstrates the performance of the minimum variance portfolio, equal weight portfolio, and market portfolio for a total of 162 days from June 12, 2023-February 5, 2024.

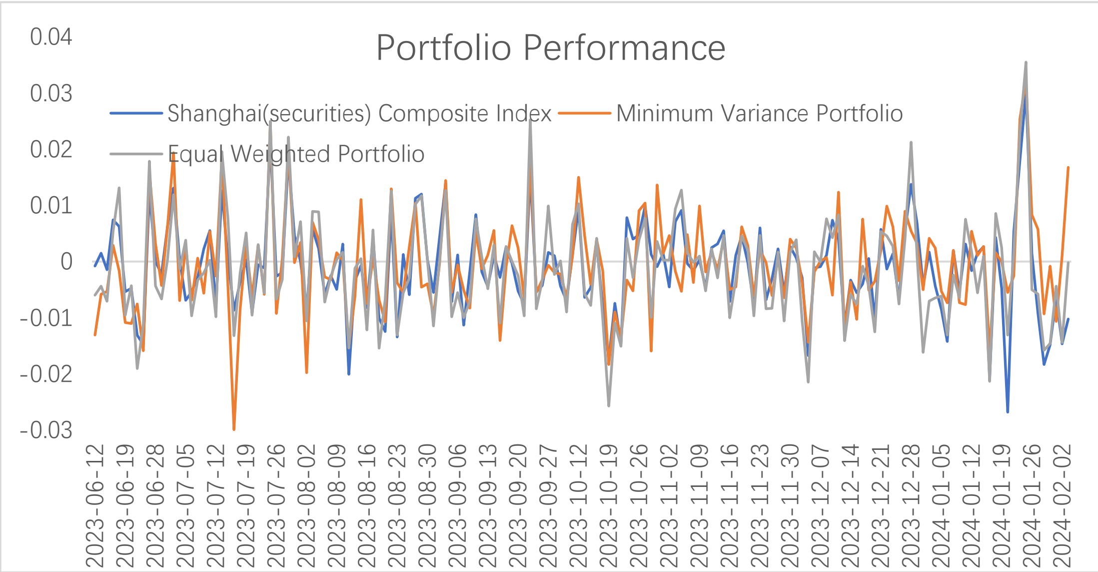

Figure 2. Portfolio performance

Considering June 12, 2023-February 5, 2024, as a whole, the minimum variance portfolio performs the best with a cumulative return of -7.88%, the SSE Composite Index is the next best with a cumulative return of -17.33%, and the equal weight model underperforms with a cumulative return of -21.74%. The negative cumulative return over the period was the result of economic uncertainty caused by the Russian-Ukrainian conflict and geopolitics.

4.2. Robustness Tests

To test the reliability of the minimum variance model, two stocks with the largest and smallest weights in the minimum variance portfolio, 601988 and 601669, are eliminated, and the asset portfolio is reconstructed by utilizing the remaining nine stocks, and the weights of each asset are shown in the Table 4 below.

Table 4. Weights in Robustness Tests

Stock Code	Weight
600028	0.3513
600048	0.0623
600050	0.0607
600111	0.0849
600519	0.1680
600887	0.1476
600905	0.0823
603259	0.0347
688111	0.0082

The reconstructed asset portfolio has the largest weight of 600028 at 35.13%, the second largest weight of 600519 at 16.80%, and the smallest weight of 688111 at 0.82%. The reconstructed asset portfolios have essentially the same day-by-day return trends for the equal-weight model and the market portfolios (See Fig. 3); and the minimum variance portfolio has the highest cumulative return at -14.24%, the SSE Composite Index is next at -17.33% and the equal-weight portfolio is the lowest at -25.62%. The results still hold for the three portfolios with the same ordering and closer returns.

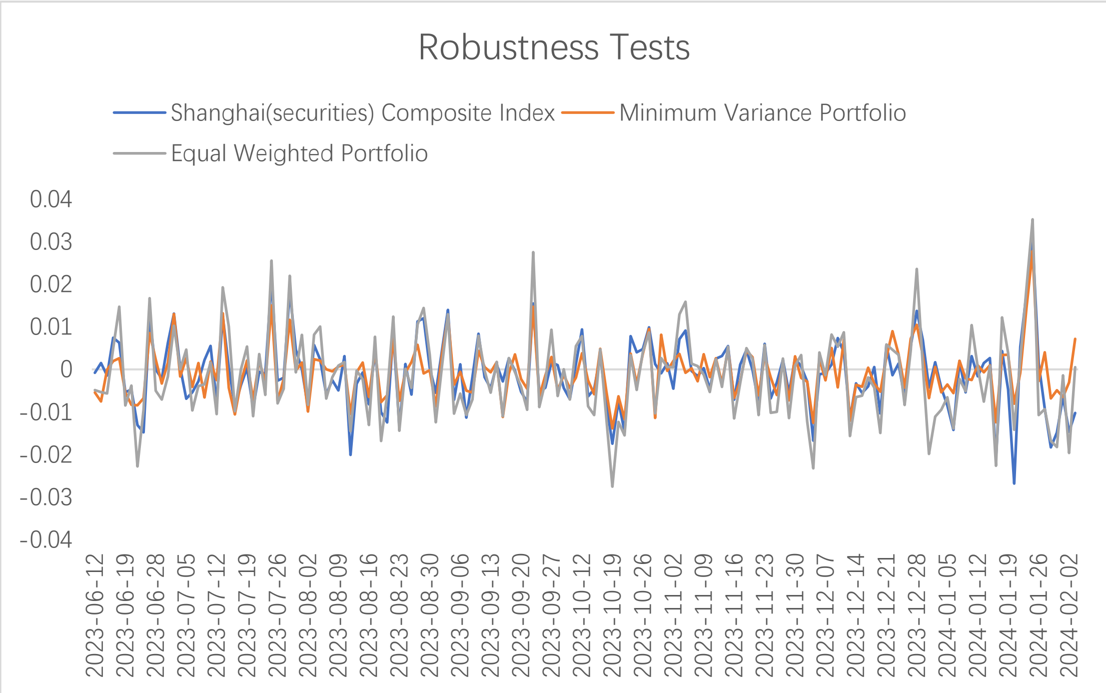

Figure 3. Portfolio performance in robustness tests

5. Conclusion

This paper uses Monte Carlo simulation and mathematical and statistical methods to study 11 leading stocks in 11 industries in China's A-share market and constructs portfolios to achieve an equilibrium of risk and return. The paper finds that the minimum variance portfolio has the largest weighting of 601988 (Bank of China) and it outperforms the market portfolio represented by the SSE Composite Index. The results remain robust when the two stocks with the largest and smallest weights in the portfolio are excluded.

Although this paper provides a solution for diversifying risk in the Chinese stock market, there is still room for additional refinement in the dimensions considered. For example, the paper assumes that all investors are risk-neutral and economic policy uncertainty impact on the stock market is not captured in the portfolio. This paper only constructs portfolios based on Monte Carlo simulation and mean-variance modeling, and in the future, more indicators can be considered as determinants of weights to make the portfolios better ahead of market performance.

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