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Portfolio Optimization for Entertainment Industry in Chinese Capital Market

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Abstract: Building an investment portfolio is one of the most common ways for investors to hedge their risks. This paper examines the investment market in China's film and entertainment industry by selecting five leading A-share companies in the film and entertainment industry. Five representative stocks from these industries were selected for analysis in this paper: Guomai Culture & media Co., ltd., Beijing Funshine Culture Media Co., Ltd., Mango Excellent Media Co., Ltd, ZHEJIANG HUACE FILM & TV CO., LTD, Alpha Group. The closing price data of these five stocks in the past year were selected and 4000 different portfolios were simulated using the Monte Carlo simulation method. Then, the mean-variance model was used to select the portfolio with the maximum Sharpe ratio and the portfolio with the minimum variance. After the weights of the two groups of assets are obtained, this paper uses the actual income data for the last month to test the performance of the portfolios. The results show that ZHEJIANG HUACE FILM & TV CO. have the largest weights in both the maximum Sharpe ratio model and the minimum variance ratio model, but the evaluation of the weights shows that the large-cap results perform better than the above model.

Keywords: Entertainment industry, China, portfolio optimization

1. Introduction

Portfolio construction is a crucial part of investment activities, which involves asset allocation, risk management and return expectations. By constructing a diversified portfolio, you can achieve effective asset allocation and optimization, reduce overall risk and increase investment return. At the same time, effective portfolio construction can also help investors to develop personalized investment plans according to their own investment objectives and risk tolerance, so as to achieve long-term and steady wealth growth and asset preservation. Therefore, investors should pay attention to portfolio construction, pay attention to the balance of risk management and return expectations, and make full use of modern investment tools and strategies to achieve effective portfolio management and optimization.

There is a wealth of relevant research on portfolios, of which the following are some examples: Ding, Liu, and Luo proposed a novel stochastic dominance-based optimization approach for portfolio selection that can outperform traditional mean-variance optimization methods [1]. Wu, Song, and Li focused on portfolio selection using mean-variance and risk measures and developed an algorithm that incorporates these factors [2]. Luo, Ding, and Wang used a hybrid differential evolution algorithm with dynamic adjustment strategy to optimize portfolios [3]. Liang, Wei, and Xu developed an optimized particle swarm algorithm for portfolio optimization problems [4]. Liu, Yao, and Su

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proposed an approach that utilizes an augmented covariance matrix to perform portfolio optimization [5]. Lawrance and Vetzal used stochastic linear programming approaches for multi-period portfolio optimization [6]. Chen and Lee focused on portfolio optimization with stochastic interest rate and inflation rate [7]. Zhang, Wang, Yang, and Yao proposed a discrete cuckoo search algorithm for constrained nonlinear integer portfolio optimization problems [8]. Huang, Lin, and Yu developed clustering-based portfolio optimization with constraints on tracking error and transaction cost [9]. Jiang and Yao presented a novel portfolio optimization approach based on model order reduction [10]. These studies provide investors with theoretical underpinnings and practical portfolio guidance to help them design more strategic and long-term portfolios for individualized, sustainable asset growth.

To date, however, there has been relatively little research comparing who performs better and who performs worse across models. This study uses two strategies - maximum Sharpe and minimum variance - to optimize portfolios and compares the results with the broader market. In this paper, the data of five shares of Chinese listed entertainment companies were analyzed. For this purpose, the stock data provided by RESSET and TUSHARE for the whole year 2022 were used and Python was applied to calculate the variance and Sharpe ratio and to construct the efficient frontier. The results show that ZHEJIANG HUACE FILM & TV CO. has the largest weighting in both the maximum Sharpe ratio model and the minimum variance ratio model. However, for portfolios constructed, neither minimum variance models nor maximum Sharpe models outperform the market and buying market indices is a good choice for future investment activities.

2. Data and Methods

2.1 Data

The data of this paper comes from The Resset, and this paper selects the representative enterprises of the following five industries as examples (See Table 1),

Table 1: Selected stocks.

Stock Code	Company
301052	Guomai Culture&media Co.,ltd.
300860	Beijing Funshine Culture Media Co., Ltd.
300413	Mango Excellent Media Co.,Ltd
300133	ZHEJIANG HUACE FILM & TV CO.，LTD
002292	Alpha Group

These 5 stocks are from five leading Chinese listed entertainment companies in the film and television sector. The reason for choosing these stocks is that their companies are leaders in their industries with high market share and brand recognition, so investing in these companies may result in higher yields. Meanwhile these companies have strong financial strength and stable business models, which are factors that can reduce investment risks. Besides they have strong competitiveness and growth potential in the digital entertainment sector, which is also a good reason to invest in these companies. These companies have high reputation and attention in the industry. Investing in these companies can bring more attention and market fever and can also bring more opportunities for investors. The last year of closing price data, from October 1, 2022, to January 1, 2023, was selected for further cleaning and disposal, resulting in a final collection of 252 entries. In this paper, these data are divided into two parts. First, 252 data from October 1, 2022, to January 1, 2023, were used to find the optimal portfolio, and 41 data from January 2, 2023, to February 1, 2023, were used to check the performance of the portfolio. After analyzing and calculating these data, the following basic information emerges for this document (See Table 2, Table 3 and Fig. 1):

Table 2: Descriptive statistics of these selected assets.

	301052	300860	300413	300133	002292
Mean	0.0005	0.0054	0.0018	-0.0001	0.0004
Variance	0.0015	0.0018	0.0011	0.0008	0.0005
Max	0.2001	0.2000	0.0911	0.0453	0.03670
Min	-0.0894	-0.0528	-0.1009	-0.1104	-0.0579

As the table shows, the average return on these data is highest at 300860 and lowest at 300133. The variance of these data is highest with 300860 and lowest with 002292. In addition, the maximum return c is 301052 and the minimum return is 300133. These results were visualized, and it was found that 300860 had the highest cumulative return over the three months, while 300133 had the lowest cumulative return.

Table 3: Covariance matrix.

	301052	300860	300413	300133	002292
301052	0.362	0.088	0.070	0.066	0.100
300860	0.088	0.404	0.122	0.096	0.100
300413	0.070	0.122	0.217	0.077	0.097
300133	0.066	0.096	0.077	0.097	0.078
002292	0.100	0.100	0.097	0.078	0.109

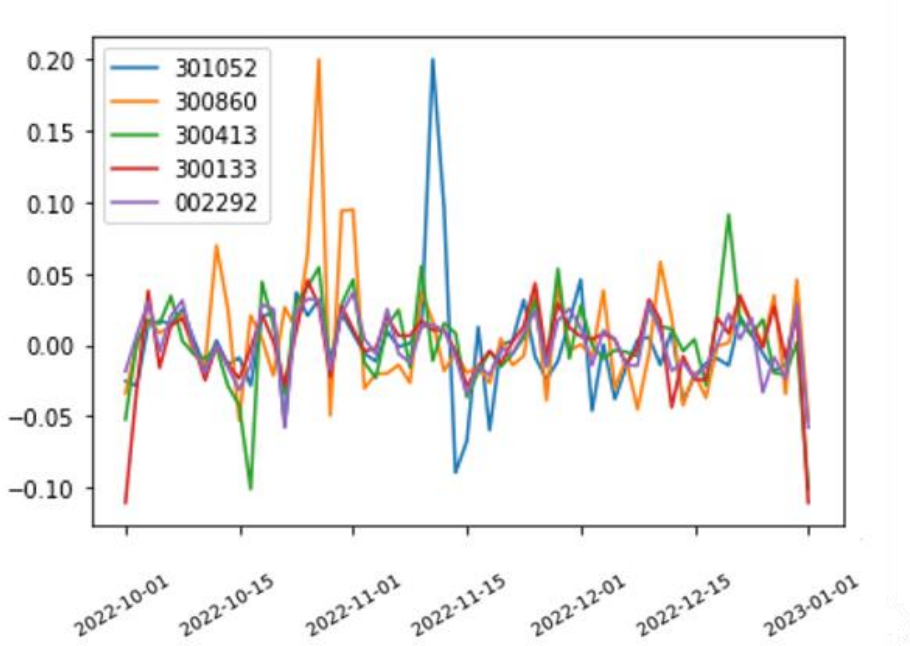

Figure 1: Cumulative returns of selected stocks.

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These results were visualized, and this paper found that basically, in these 3 months, 300860 has maintained the highest cumulative income, while 300133 has the lowest cumulative income.

2.2 Method

The process can be done by the weighted average method. This method multiplies the return of each asset by its weight in the portfolio and then adds up the weighted returns of all assets to obtain the total return of the portfolio. Where the weights are determined by factors such as the market value of each asset in the portfolio or the amount invested.

The specific calculation formula is as follows:

$$\begin{gathered} Return\ Rate\ Vector:\ R=(r_1,r_2,\ldots,r_{\mathrm{i}})^T \\ Weight\ Vector:\ W=(w_1,w_2,\ldots,w_{\mathrm{i}})^T \\ Expected\ Return\ of\ Portfolio: \mathrm{E}(R_P)=W^TR=\sum_i w_i r_i \\ \sum_i w_i=1 \end{gathered} \tag{1}$$

Where, w_i is the weight of asset i, r_i is the return of asset i. The rate of return of asset i can be calculated from the change in asset value and dividends, among other factors. The total return of the portfolio can be used as an important indicator of portfolio performance, which reflects the combined performance of all assets in the portfolio.

The process for calculation the variance of the portfolio involves two steps. First, the covariance matrix of each asset, i.e., the correlation between the assets, needs to be calculated. The covariance represents the degree of linear correlation between two random variables, and when the covariance is positive, it indicates a positive correlation between the two variables, and when the covariance is negative, it indicates a negative correlation between the two variables. Next, the variance and standard deviation of the portfolio are calculated using the covariance matrix and the weights of each asset in the portfolio. The specific calculation formula is as follows:

$$Variance: \sigma_P^2=\operatorname{var}\left(\sum_i w_i r_i\right)=\sum_{ij} w_i\, w_j \operatorname{cov}(r_i r_j) \tag{2}$$

Where the weights and covariances of asset i and asset j can be calculated from historical data or other methods. The standard deviation of a portfolio is an important indicator of the volatility risk of a portfolio, which can help investors assess the risk level of a portfolio and thus make more informed investment decisions.

The higher the expected return of the investment target, the higher the volatility risk that the investor can endure; Conversely, the lower the expected return, the lower the volatility risk. Therefore, the main purpose of rational investors in choosing investment targets is to pursue the maximum return under the fixed risk they can bear; Or pursue the lowest risk under a fixed expected reward.

The Sharpe ratio (also known as the Sharpe Index) is such a classic indicator that can combine both return and risk. It was first proposed by Nobel laureate William Sharp in 1966.

$$Sharp\ Ratio=\frac{E(R_P)-R_f}{\sigma_P} \tag{3}$$

Where, E(Rp) indicates the expected return on the portfolio, Rf stands for Risk-Free Rate, σ_P represents the standard deviation of the portfolio [11]. The efficient frontier is the boundary line that minimizes risk for a given level of expected return that can be achieved in a given portfolio. The efficient frontier is a curve consisting of all possible portfolios, and each point on that curve represents the portfolio with the lowest risk for a given set of assets or portfolio. The construction of the efficient frontier is based on modern portfolio theory, in which it is assumed that investors make investment decisions by considering the trade-off between the risk and return of a portfolio in order to achieve the most optimal investment objective.

The construction of the efficient frontier requires consideration of the correlation and risk characteristics among various assets, as well as the investor's risk appetite and expected rate of return. By calculating the risks and returns of various portfolios, the efficient frontier can be drawn. The points on the efficient frontier represent the most optimal portfolio, i.e., the portfolio with the least risk for a given level of expected return.

The study and construction of the efficient frontier is important for investors and investment institutions to help them optimize portfolio allocation, improve portfolio returns and reduce risks. In practice, the construction of the efficient frontier needs to take into account factors such as the authenticity and validity of data, as well as investors' risk preferences and investment objectives.

3. Results

First, this paper simulates the results of 4,000 differently weighted portfolios using the Monte Carlo method based on return data for five stocks for the period from October 1, 2022, to January 1, 2023, and plot the expected returns and volatility of these portfolios in the same graph, as shown below in Fig. 2:

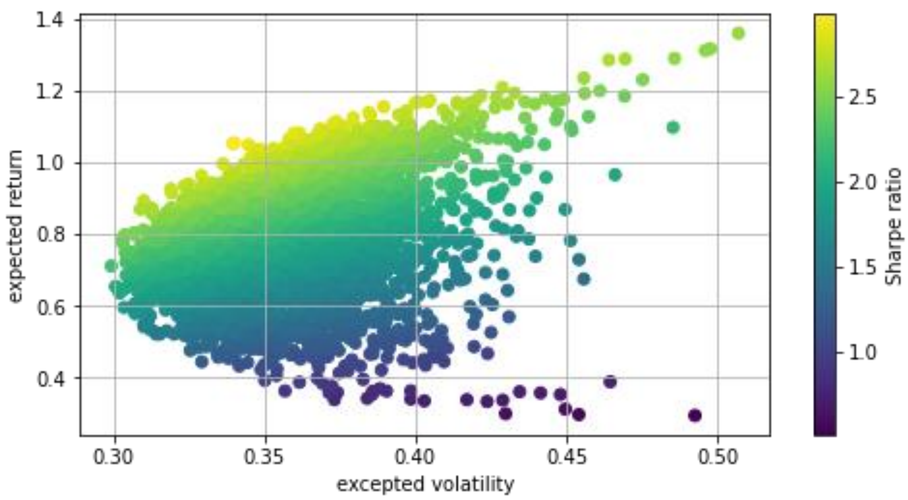

Figure 2: Efficient frontier retrieved by Monte Carlo method.

As shown in the graph, these results form a sector called the efficient set, and the boundary of the efficient set curve is called the efficient frontier. Based on this graph and the mean variance model, the optimal portfolios can be determined, namely the portfolio with the maximum Sharpe ratio and the portfolio with the minimum variance. They can be interpreted as the portfolio with the largest excess return per unit risk and the portfolio with the lowest risk in the above efficient set. The calculated portfolio weights as well as the Sharpe ratio and variance are shown in the following Fig. 3 and Table 4:

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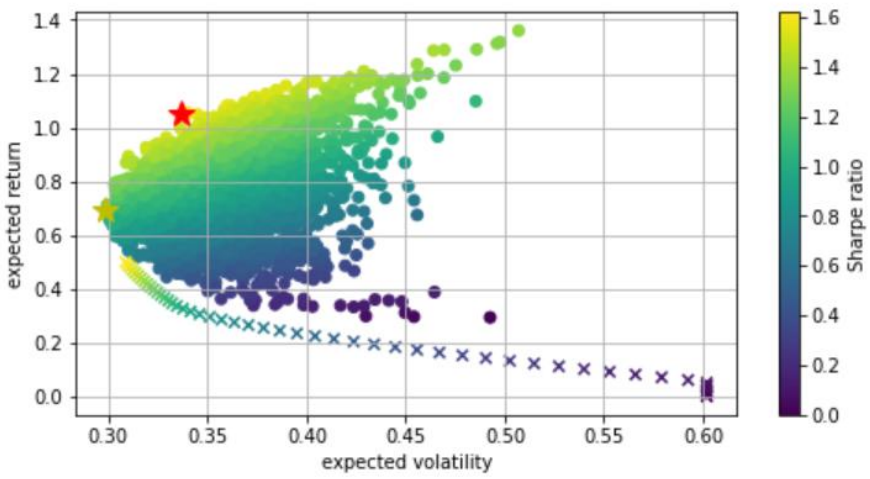

Figure 3: Asset weights under two criterions.

Circles: Monte Carlo randomly generated combinatorial distributions
Cross: Effective Frontier
Red Star: Mark the highest Sharpe ratio combination
Yellow Star: Marks the least variance combination

Table 4: Asset weights under two criterions.

	301052	300860	300413	300133	002292
Maximum Sharpe Ratio	0	22.5%	16.7%	60.8%	0
Minimum Volatility	4.3%	0	4.7%	60.6%	30.3%

Weights of the two interested portfolios are shown in Table 4. As can be seen, the results of the two portfolios are very different. In the maximum Sharpe ratio portfolio, 300133 has the largest weight of 60.8%, while 301052 and 002292 have the smallest weight of almost 0. In the minimum variance portfolio, 300133 has the largest weight of 60.6%, which is already more than half of the whole portfolio, but the lowest weight is 300860, which is almost 0. These two portfolios are compared to 300860 and 002292 have very different weights, while 300133 has the same larger weight in both portfolios.

After getting the weights of each asset in the portfolio, in order to verify the performance of the best portfolio, this paper uses the real closing price data from January 2 to February 1, 2023, and applies the respective weights in the best portfolio to get the real risk and return performance of the best portfolio in these two months and compares it with the Shenzhen Stock Composite Index. The Shenzhen Stock Composite Index is a composite index of all stock prices on the Shenzhen Stock Exchange, and it is considered to be the market level of A-shares. The optimal portfolio will be considered efficient if its return in these two months is greater than the Shenzhen Stock Composite Index.

For the maximum Sharpe ratio portfolio, this paper calculates the cumulative returns of this portfolio and the Shenzhen Stock Composite Index, and the results are 3.39% and 2.512%, respectively, which implies that the maximum Sharpe ratio portfolio outperforms the market level of returns (See Fig. 4 and Fig. 5).

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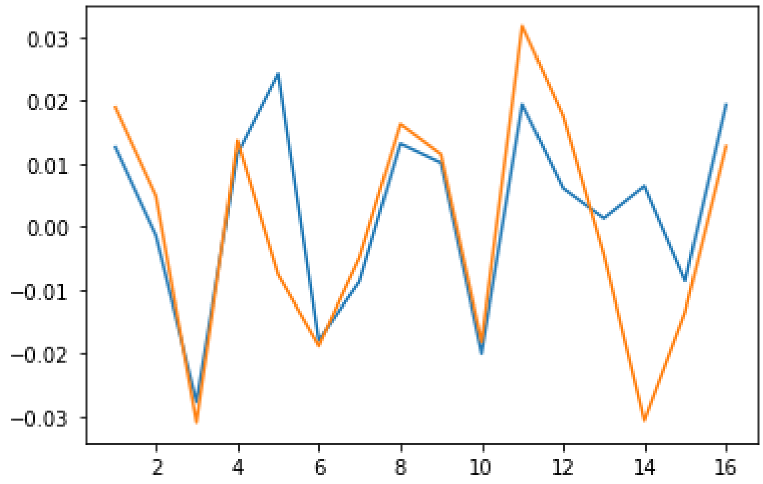

Figure 4: Comparison of maximum Sharpe ratio portfolio and the market level.

Blue line: market yields
Yellow line: maximum Sharpe ratio
However, for the minimum variance portfolio, the cumulative return of the portfolio is 2.71%, not much difference from market yields.

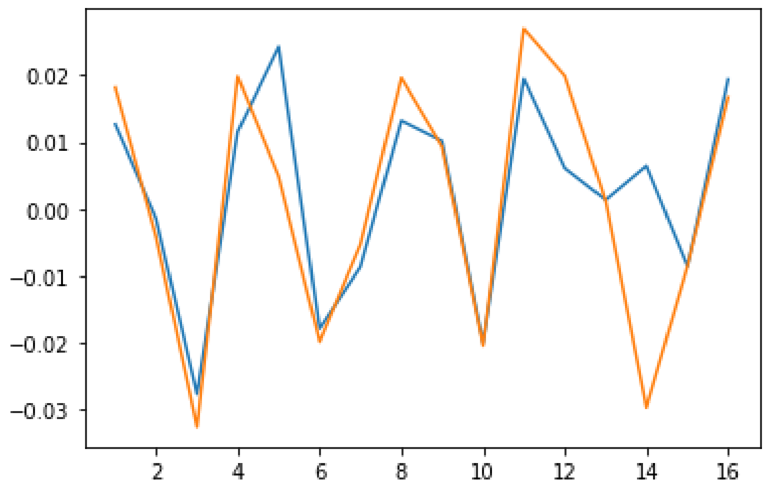

Figure 5: Comparison of minimum variance portfolio and the market level.

Blue line: market yields
Yellow line: minimum variance

4. Conclusion

This paper examines a single-sector portfolio. In this paper, thousands of different portfolios are simulated using Monte Carlo simulation to obtain an efficient set of all possible portfolios. The portfolios are then optimized using a maximum Sharpe ratio model and a minimum variance model, respectively. The results show that ZHEJIANG HUACE FILM & TV CO. have the largest weights in both the maximum Sharpe ratio model and the minimum variance ratio model better results are obtained with the maximum Sharpe value strategy compared to the minimum variance strategy. However, portfolios constructed using mean-variance models do not outperform the market, and buying market indices is a good choice for future investment activities.

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