

Portfolio Optimization Based on 5 Hong-Kong Stocks

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Abstract: The recent fluctuations in interest rates in the Hong Kong stock market have sparked a significant amount of attention, prompting investors to further intensify their research into portfolio optimization strategies. To determine the most suitable investment plan, this study carefully selected five Hong Kong stocks based on their market capitalization. Predictive data were utilized for portfolio optimization, with the mean-variance analysis framework used to measure portfolio performance. Our model revealed that asset allocation of 2800.HK held the highest proportion in the minimum variance model, with the five stocks holding ratio of 0.119952, 0.000517, 0.067936, 0.030762, and 0.822611 separately. The average cumulative return using mean variance on the testing dataset was 1.091263. The final findings of this study may be useful to investors seeking to optimize their investments in the Hong Kong stock market. The insights gained from this research could help investors make better decisions and achieve improved returns.

Keywords: portfolio optimization, mean-variance, Hong Kong stock market

1. Introduction

In 1952, Markowitz first presented the mean-variance model, which is one of the most popular areas of research in the field of finance has been the optimisation of investment portfolios [1]. Natural investors typically have a low risk tolerance and a strong aversion to loss because of the small quantity of wealth they have available to invest. As a result, one of their primary concerns is unquestionably figuring out how to maximise profits while minimising risk to the greatest extent feasible [2-4]. As a result, striking a healthy balance between the potential for profit and the potential for loss is undeniably an intriguing research topic in the field of finance. In other words, making judgements about one's portfolio is in one's interests. In addition, investors in the company are required to invest in a diversified portfolio rather than just one asset as part of their investment strategy. Because utilising these various strategies will assist in lowering the overall risk [5].

Investment portfolio research has always been a hot topic in the financial field [6,7]. In recent years, with the emergence of new technologies, more and more scholars have begun to use machine learning, big data, and artificial intelligence technologies to study investment portfolios. The following are some important research results in recent years: Li et al. established a meta-learning-based investment portfolio optimization model, used historical data to train the model, and demonstrated the effectiveness of the model in empirical analysis [8]. Siarheyeva et al. classified stocks from multiple dimensions such as credit ratings, yields, and liquidity based on big data technology, and based on this, constructed a multi-factor stock selection model to optimize investment portfolios [9].

Zhou et al. investigated and analyzed the characteristics of fund managers in different countries, established an investment portfolio construction model based on the characteristics of fund managers for cross-border investment, and achieved good performance in tracking error and returns [10]. Chen et al. proposed a pair trading strategy based on convolutional neural network, analyzed the historical price data of multiple stocks, automatically discovered paired trading opportunities, and effectively reduced the risk of investment portfolios [11]. He et al. proposed a dynamic asset allocation strategy based on factor models and Markov chain Monte Carlo method, automatically judged the factor attributes of stocks in massive data, and realized optimized allocation of different asset categories [12]. In conclusion, investment portfolio research has been constantly emerging with new ideas and methods under the driving force of emerging technologies. In the future, with the continuous development and application of technology, investment portfolio research will usher in broader development prospects.

This study will investigate how effective asset allocation optimisation is and will offer individual investors a reference for managing their portfolios throughout this unique time period. A Python module known as "yfinance" is used to download the portfolios, each of which consists of five different stocks. Two distinct subsets, the training set and the testing set, have been derived from the dataset. The investigation revealed that each of the three selected portfolios outperformed the index for the time period under consideration.

The following is the structure of this piece of writing: Section 2 introduces the stocks that were chosen and the data that was used in the study. In Section 3, the process of constructing the model and determining the optimal portfolios is broken down and explained. In Section 4, the results will be presented, and then in Section 5, the conclusion and the discussion will be presented.

2. Data

This paper selects top 5 representative stocks according to the market capitalization from the Hong Kong Stock Exchange. The ticker of the 5 stocks are '0005.HK', '0006.HK', '0066.HK', '0700.HK', '2800.HK'. Closing prices from November 23rd 2021 to June 21st 2022 are collected and separated into training set and test set. The training set is used for calculating the average return and covariance matrices in order to construct the efficient frontier. The test set is for evaluating the performance of the selected asset allocations by comparing their cumulative returns to the Hong Kong Index return. The basic information of the 5 chosen stocks is presented in Fig. 1, Table 1 respectively.

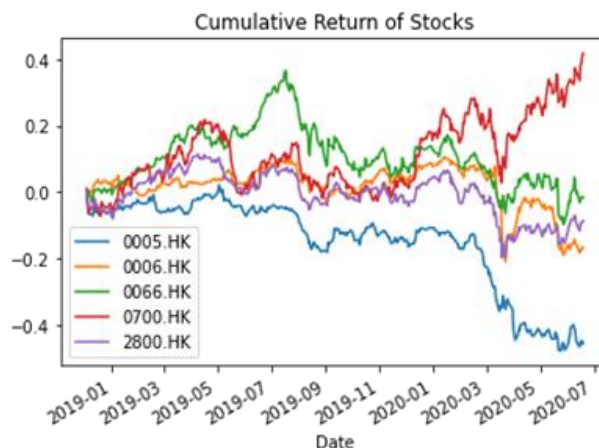


Figure 1: Cumulative returns of 5 selected stocks.

Table 1: Descriptive statistics of the daily return of the 10 stocks.

	0005.HK	0006.HK	0066.HK	0700.HK	2800.HK
count	162.0000	162.0000	162.0000	162.0000	162.0000
mean	0.0102	0.0321	-0.0043	-2.2500	
std	0.4923	0.3908	0.4589	12.6494	
min	-1.1500	-1.2500	-1.9500	-43.5000	
25%	-0.3000	-0.2375	-0.2500	-9.8750	
50%	-0.0500	0.0500	-0.0500	-3.0000	
75%	0.3000	0.2875	0.2500	5.0000	
max	1.6000	1.3000	1.3000	59.5000	

Fig. 1 reveals that 0700.HK presents the highest cumulative return of 40.24%, whereas the cumulative return of 0006.HK increased with fluctuation and reaching -21.30% in the end.

Table 2: Correlation between each stock.

	0005.HK	0006.HK	0066.HK	0700.HK	2800.HK
0005.HK	1.000000	0.350040	0.215240	0.029210	
0006.HK	0.350040	1.000000	0.385853	-0.145420	
0066.HK	0.215240	0.385853	1.000000	0.096511	
0700.HK	0.029210	-0.145420	0.096511	1.000000	
2800.HK	0.381661	0.090697	0.328997	0.712916	

3. Methods

In this paper, the mean variance model is used. The mean variance model examines the balance between the portfolio expected return and the risk. The portfolio return and the variance are as follows:

$$\mu_p = \sum_i w_i \mu_i \quad (1)$$

where w_i is the i^{th} component weight of the portfolio, μ_i is the expected return of the i^{th} component.

$$\sigma_p^2 = \sum_i \mu_i^2 w_i^2 + \sum_i \sum_j \sigma_i \sigma_j w_j w_i \rho_{ij} \quad (2)$$

where σ_i is the standard deviation of the asset i returns, and ρ_{ij} is the correlation coefficient between the returns on assets i and j . Therefore, calculating the average return and the covariance matrix of the stocks is essential.

In order to generate a variety of portfolios, the Monte Carlo simulation is utilised. This technique helps imitate the operation process as random ones under specified conditions and by employing

given parameters; the parameters utilised in this study were the stocks' average return and covariance matrices. Then it is possible to calculate the expected return of the portfolio and the variance of the portfolio based on the weights if one uses a stochastic method to generate the weights for each item in the portfolio. The data pool would be representative for the vast majority of conceivable asset allocations if one were to repeatedly simulate one hundred thousand portfolios in the same manner. This would allow one to use the data pool to sketch out the efficient frontier.

4. Results

The Monte Carlo approach had been used to successfully complete 100,000 different simulations. The sub-optimal portfolios can be found below the efficient frontier (see Fig. 2). These portfolios offer a return that is lower than average for the level of risk that is being taken.

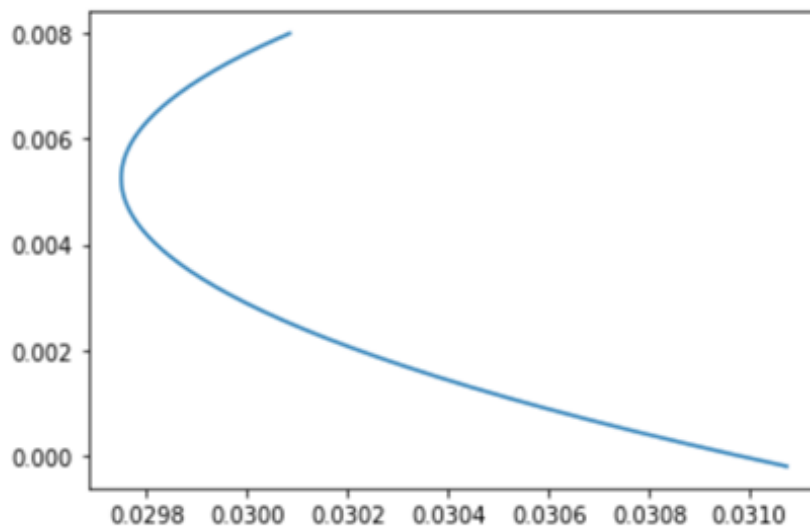


Figure 2: Efficient Frontier.

This paper has searched for the minimum variance investment portfolio on the efficient frontier, and found the corresponding investment ratios of each asset in this portfolio listed in Table 3.

Table 3: Ratio of each stock.

Stock name	Ratio
0005.HK	0.119952
0006.HK	0.000517
0066.HK	0.067936
0700.HK	0.030762
2800.HK	0.822611

After that, the strongest portfolios will be chosen. Fig. 3 displays the estimated results for the test dataset the cumulative return using mean variance on testing dataset.

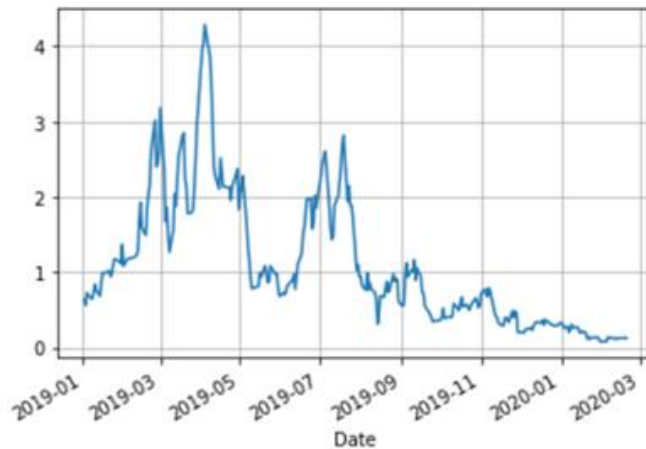


Figure 3: Cumulative return using mean variance on testing dataset.

Therefore, the method and the results are valid and effective.

5. Conclusion

In a nutshell, the purpose of this study was to analyse the mean-variance analysis, which is utilised in the process of portfolio optimisation. After that, the Monte Carlo simulation was used to generate one hundred thousand different random portfolios, and then the calculation of the return and volatility of the portfolio was performed. The data was visualised by graphing the portfolio return against the volatility, which allowed for the efficient frontier to be identified. Then, the author searched for the minimum variance investment portfolio on the efficient frontier, and found the corresponding investment ratios of each asset in this portfolio. This paper suggests that when there is a bearish outlook for the stock market, it is possible that this asset allocation approach will be preferred and recommended.

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