

Markowitz-Based Portfolio Research

Yuyang Lin^(IM), Guoxi Su, Jingrui Pan, and Pengtao Zhang

Macau University of Science and Technology, Taipa, China 2227931285@qq.com

Abstract. Stock investment, as an investment behavior, faces various situations of unknown uncertainty, therefore, it is very important to reduce the unsystematic risk of stocks and eliminate uncertainty by various means and technical methods for investing in stocks. In this paper, we will use python and the data of listed companies in CSMAR database to construct the Markowitz portfolio model to study the risk and return problem in stock portfolio based on Markowitz portfolio theory. The paper also uses the empirical analysis in A-share market to show that Markowitz portfolio theory can effectively reduce the risk while obtaining the return.

Keywords: Equity · Investment · Portfolio Model

1 Introduction

In 1952, Markowitz first proposed the theory of investment portfolios by publishing a paper in the Journal of Finance entitled "Selection of Portfolios - Effective Diversification of Investments". This also marked the official birth of Modern Portfolio Theory (MPT). His theories mainly include mean-variance analysis methods and portfolio effective frontier models, which effectively solve the problem of asset selection. This theory proved effective in practice and is considered the beginning of modern finance, for which he won the Nobel Prize in Economics in 1990. Markowitz's portfolio provided a guide for reducing risk and increasing returns, opening the way for what is now financial engineering [1]. In the West, stock portfolio has been widely promoted as a very effective investment method, and portfolio theory has played a very important role in the stable development of Western capitalist countries. Therefore, this paper will apply the Markowitz mean-variance theory to study the risk and return issues in stock portfolios [2]. Below we will use public company data from Python and CSMAR databases to build the Markowitz portfolio model [3].

2 Model Review

2.1 Expected Return for a Single Asset

$$E(r) = \sum_{i=1}^{n} p_i r_i$$

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K. Hemachandran et al. (Eds.): ICAID 2023, AHIS 9, pp. 290–295, 2023. https://doi.org/10.2991/978-94-6463-222-4_30 Note: The future rate of return of an asset is random, and each different rate of return Ti is affected by a different market environment and the probability of occurrence of different market environment is Pi [4]. The reason for randomness is that the information appears randomly, and when a new information appears, a new price will appear, so the future price of an asset may have countless possibilities. That is, there are countless price states in the future of the asset, and the rate of return of each price state is Ti, the probability of this rate of return appearing is Pi, and the product of all the probability and return is the expected return of the asset [5].

2.2 Risk of Individual Assets

$$G^2 = \sum_{i=1}^{n} p_i [T_i - E_r]^2$$

Note: The risk of a certain asset is the average degree to which the return on investment deviates from the expected value. Therefore, the risk is expressed by the variance or standard deviation of return [6].

2.3 Expected Return of Portfolio Investment

$$\sum_{i=1}^{n} w_i = 1$$
$$E(TQ) = \sum_{i=1}^{n} w_i E(\Pi)$$

Note: When using historical data, we believe that the expected return of portfolio is the weighted average of the expected return of all securities, and the weights are the proportions of their investments.

2.4 Portfolio Risk

$$G_Q^2 = \sum_{i=1}^{n}$$
$$\sum_{j=1}^{n} w_i w_j \text{cov}(T_i, T_j) = WT \sum w$$

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Note: Portfolio risk is the weighted sum of the covariance of each asset in the portfolio, and the weight is the product of a pair of assets in the portfolio within the covariance [7].

2.5 Key Concept

1. Feasible set: The set of all possible investment portfolios faced by investors.

Solution: Transform the weight of each asset in the portfolio, consider all possible weights, and simulate the standard deviation and expected return rate of each portfolio under different correlation coefficients. The standard deviation is placed in the abscissa and the expected return is placed in the ordinate to obtain the feasible set [8].

2. Valid combination frontier: The point set of the maximum expected return or the minimum risk level in the feasible concentration under the given risk level faced by all investors.

3. The Capital Market Line (CML): A ray that indicates a simple linear relationship between the expected return and the standard deviation of an efficient portfolio. It is a portfolio consisting of risky and risk-free assets along the efficient frontier of the portfolio.

4. Sharpe ratio:

$$SharpRatio = \frac{E_{rQ} - R_f}{\sigma_O}$$

Note: Rf is risk-free interest rate. When Sharpe ratio is the largest, it is the tangent line between risk-free assets and effective frontier, that is, the slope of the capital market line. It also represents the compensation for unit risk, indicating that investors are willing to bear the additional returns required for each unit risk.

5. Fund separation theorem: On the effective frontier of risk portfolio, any two separated points represent two separated effective risk portfolios; In addition, on the efficient frontier, any other point can represent a portfolio generated by the combination of these two separate portfolios.

3 Empirical Results

We selected 5 liquor stocks in the same sector of A-share, namely, Kweichow Moutai, Wuliangye, Yanghe, Luzhou Laojiao and Gujing Gongjiu, as the observation targets, and the observation period was from Oct. 18, 2019 to Oct. 18, 2022.

Make a stock trend chart with python: Fig. 1.

We therefore find that the return and risk of the portfolio with one random weight is: 0.21 and 0.335, and the average risk of the portfolio with 100 random weights is: 0.349. We then select the return and risk of the portfolio with the largest Sharpe ratio out of 3000 random weights is: 0.30 and 0.392, and the return and risk of the portfolio with the smallest risk is: 0.166 and 0.303.

Then we selected five stocks from different sectors, that is, Kweichow Moutai, CATL, Yili Shares, Ping An Bank, and SANY Heavy Industry, as the observation targets.

The trend chart of individual stocks is shown in Fig. 2.

We therefore find that the return and risk of the portfolio with one random weight is: 0.241 and 0.271, and the average risk of the portfolio with 100 random weights is: 0.266. While the return and risk of the portfolio with the largest Sharpe ratio out of 3000 random weights selected is: 0.578 and 0.396, the return and risk of the portfolio with the smallest selected risk is: 0.094 and 0.239 [9].



Fig. 1. Stock chart



Fig. 2. Stock chart

4 Conclusion

Based on the results of the above data, we find that.

- 1. 5 stocks in the same wine sector, Kweichow Moutai, Wuliangye, Yanghe, Luzhou Laojiao and Gujing Gongjiu, have an annualised risk of 0.399, with a minimum risk of 0.303 selected after 3000 Monte Carlo simulations, normalised to reduce (0.399 0.303)/0.399 = 0.241 = 24.1%.
- 2. 5 stocks in different sectors, Kweichow Moutai, Ningde Times, Yili, Ping An Bank and Sany Heavy Industry, with an annualised risk of 0.369, have a minimum risk of 0.239 after 3000 Monte Carlo simulations, which is a normalised reduction of (0.369 0.239)/(0.369 = 0.352 = 35.2%).
- 3. The same sector is reduced from an equal weight of 0.399 to 0.303, a reduction of 24.1%, and 0.303 is significantly lower than the risk of a separate position in most individual stocks; stocks in different sectors are reduced from an equal weight of 0.369 to 0.239, a reduction of 35.2%, and we find that 0.239 is significantly lower than the risk of a separate position in most individual stocks.
- 4. Based on our data selection, the reduction in risk increases from 24.1% to 35.2% as we gradually move from a portfolio of highly correlated equity assets to a portfolio of less correlated equity assets. Thus, the above comparisons and tests provide preliminary evidence that coefficient adjustments for portfolios between less correlated individual stocks will result in significant improvements in portfolio risk without significantly affecting returns. Our study concludes that the selection of less correlated assets leads to a more significant degree of risk reduction in the portfolio.
- 5. Having a portfolio does reduce investment risk. There is no limit to the extent to which we can reduce the risk and increase the return of a portfolio's assets by combining them. However, we cannot go on indefinitely; there is a frontier, that the portfolio can never exceed. It is possible for a relatively low risk but very high return portfolio point to arise by chance, but according to arbitrage pricing theory we can assume that once an arbitrage opportunity exists, a small number of investors in the market with a large amount of capital will make the arbitrage opportunity disappear, which means that such an efficient portfolio point no longer exists [10].

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