Optimization effects in the new energy, medical and home appliance industries of China’s A-Share Market

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Abstract. Portfolio construction is increasingly prevalent in the business field and is becoming a popular concern in scientific research today. This study compares optimization effects in the renewable energy, pharmaceutical and home appliance industries of China’s A-Share Market. Mean-variance model and Sharpe ratio are implemented to ensure the expected returns and to reduce risks for portfolios at the same time. Under the assumption that there is no limitation on the short selling, it is found that market portfolio can produce higher risk-adjusted returns than the benchmark stocks in each industry. Furthermore, the optimization effects in the pharmaceutical industry were more significant than those in the renewable energy industry but less considerable than those in the household appliance industries. The main reason may be that the diversification and leverage effects perform differently in different industries. In addition, the methodologies and findings of the paper can help investors understand the optimization benefits more deeply and guide their construction of the market portfolios.

Keywords: Optimization effects, Portfolio selection, Mean-variance model, Sharpe ratio.

1. Introduction

As the economy has become increasingly globalized, China's emerging securities market has grown rapidly and created remarkable achievements. Investors tend to put more disposable incomes into stocks with the expectation for higher returns in a shorter time. However, the majority of participants in the China’s A-share market are retail investors who have little professional knowledge and limited investment experience. Domestic regulations on investment funds are also defective. Therefore, scientific portfolio selection has become a worldwide issue for researchers in the ever-evolving business environment.

Markowitz [1] proposed the basic concept of portfolio selection theory and built an optimization model that considered both returns and risks of portfolios. This so-called mean-variance model could achieve the maximum return at a given level of risk, or maximize the reduction of risk if the income is fixed [2]. A large number of studies had verified optimization effects of the mean-variance model. For instance, according to this method, the empirical research of Li [3] successfully constructed the optimal investment of 10 stocks in China's securities market. Nevertheless, the calculation of the mean-variance model was too complicated for participants without mathematical background to understand. The Sharpe ratio, which was defined as the ratio of the excess return of a portfolio to its standard deviations [4], might be an easier way to accept and apply. Taking Song [5] as an example, she analyzed the application of Sharpe ratio in investment strategy under the non-short selling condition. Investors were able to build the optimal risky portfolio simply by maximizing the Sharpe ratio. This ratio made economic sense as well and had been widely used in the academic and commercial fields.

However, most studies in China focused on the further development of the methodologies mentioned above in individual industries. Cross-industry differences of optimization effects remained unclear. Hence, it was critical to evaluate whether the optimization strategies worked efficiently in different industries of China’s stock market. Based on daily returns of 9 stocks in the new energy, medical and home appliance industries of the China’s A-Share Market, this paper used both the mean-variance model and the Sharpe ratio to build the market portfolios given the condition of no short selling constraints. It also compared the optimization benefits in the three industries, centered on the diversification and leverage effects. The research could put forward the understanding of optimization and enable investors to gain profits from the optimal risky portfolios.

2. Methods

2.1 Mean-Variance Model

Markowitz [1] proposed the theory of portfolio selection which used the mean and variance of assets' rates of returns to measure the portfolio's expected return and risk, respectively. The mean-variance model could mathematically define investors' preferences, and thus helped them rationally combine their assets.

The traditional theoretical model was based on a number of strict assumptions, mainly including [6]:

(1) Investors knew the probability distribution of each asset's return in advance. Their investment decisions only took the mean and variance of return rates into consideration.

(2) All investors in the market were rational (i.e., risk-averse).

(3) The capital market was efficient and prices accurately reflected intrinsic value of assets.

(4) *N* kinds of assets were risky and the interest rates of all assets were independent identically distributed (i.i.d).

(5)Short selling was achievable (i.e., allowing negative position).

(6) Investments in each asset were infinitely divisible and any investors were price takers.

In practice, the objective of the optimization model was to minimize risks when the expected investment value was determined, or to maximize the return on investment at certain risk [7]. The complete mean-variance model could be presented as follows:

$$\begin{gathered} min \;\; Var\,(r_p) \\ s.t.\; \overline{r_p} = \sum_{i=1}^{n} w_i\, E(r_p) \\ r_p = \sum_{i=1}^{n} w_i\, r_i \\ Var\;\;(r_p) = \sum_{i=1}^{n} w_i{}^2\;\; \sigma_i{}^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i\, w_j\, \rho_{ij}\sigma_i\sigma_j \\ \sum_{i=1}^{n} w_i = 1 \end{gathered} \tag{1}$$

r_p represented the portfolio's rate of return, $\overline{r_p}$ meant investor's expected rate of return, $Var(r_p)$ was the portfolio's variance (i.e., risk), σ_i was the standard deviation of asset_i, ρ_{ij} was the correlation coefficient between asset_i and asset_j, r_i, represented the return rate of asset_i, w_i was the proportion of asset_i, and n meant that there were n kinds of risky assets involved in the portfolio.

2.2 Sharpe Ratio

Sharpe [4] designed Sharpe ratio on the basis of Capital Asset Pricing Model (CAPM). This ratio represented the excess return per unit of total risk, reflecting the degree to which the expected return rate of the investment exceeded the risk-free rate within the unit risk. It could measure the return and risk of an asset at the same time and was commonly used to gauge the investment's performance by adjusting for the volatility. Additionally, Sharpe ratio helped investors jump out of the misunderstanding that high returns were inevitably accompanied by high risks. The problem that it is difficult to rank assets under different risks and returns was solved as well. Consequently, the highest Sharpe ratio portfolio without investing in the risk-free asset was generally considered as the optimal risky portfolio. According to the definition, the traditional Sharpe ratio could be calculated by the following equation:

$$Sharpe\ Ratio = \frac{E(r_p) - r_f}{\sigma_p} \tag{2}$$

r_f was the risk-free return (mean return of one-year time deposit on daily basis), and σ_p was the portfolio's standard deviation.

Equation (2) indicated that the excess return of the investment was greater than the risk when Sharpe ratio was higher than 1; when Sharpe ratio was lower than 1 but higher than 0, the excess return was less than the risk; there was no excess return when Sharpe ratio was equal to 0; and negative Sharpe ratio pointed out that the average return rate was even lower than the risk-free rate, implying the meaninglessness of the investment [8]. Moreover, the value of Sharpe ratio needed to be compared with assets of the same type rather than focusing on an individual asset. Under the circumstances, the higher the Sharpe ratio, the greater the excess return obtained per unit of risk, the bigger the investment value. In the past few decades, Sharpe ratio was broadly applied in the financial field and was further developed in numerous researches.

2.3 Data

This study collected data from CSMAR which is carefully designed in combination with China's national conditions. The information is authoritative and reliable since the Finance and Economics Database of CSMAR is currently the largest and most accurate domestic database. Furthermore, the benchmark assets were 9 stocks in the China's A-Share Market, specifically trading at the Shenzhen Stock Exchange. These stocks focused on three representative industries. The new energy industry was noticed because it was environmentally friendly and had continued to flourish in a favorable policy environment. The pharmaceutical industry had received a great deal of attention recently due to the Covid-19 pandemic, and the home appliance industry was a typical traditional industry. The specific benchmark stocks were listed in Table 1.

The empirical study of the paper was based on the 9 stocks' daily returns from Apr 1, 2021 to March 31, 2022. For each stock, the return rates were normally distributed and returns at different times were uncorrelated (as shown in Figure A1 and Figure A2). In other words, the i.i.d assumption was reasonable in the data. Moreover, the one-year bank time deposit was chosen as the risk-free asset. Table 2 outlined the descriptive statistics of both risky and risk-free assets.

Table 1. Benchmark stocks in three industries

Benchmark stock	Description
New energy industry	
tsfn	Titan Wind Energy (Suzhou) Co., Ltd.
sygf	Shandong Sacred Sun Power Sources Co., Ltd.
akkj	Jiangsu Akcome Science & Technology Co., Ltd.
Pharmaceutical industry	
lszy	Tianjin Lisheng Pharmaceutical Co., Ltd.
dcyy	Yantai Dongcheng Pharmaceutical Group Co., Ltd.
khyy	Sunflower Pharmaceutical Group Co., Ltd.
Home appliance industry	
lbdq	Hangzhou Robam Appliances Co., Ltd.
zjmd	Zhejiang Meida Industrial Co., Ltd.
xbgf	Guangdong Xinbao Electrical Appliances Holdings Co., Ltd.

Table 2. Descriptive statistics of selected assets

Asset	Min	1st Qu	Median	Mean	3rd Qu	Max	Std Dev
tsfn	-0.1001	-0.0208	-0.0012	0.0022	0.0195	0.1004	0.0383
sygf	-0.1001	-0.0187	0.0000	0.0016	0.0178	0.1007	0.0368
akkj	-0.1008	-0.0173	-0.0039	0.0020	0.0182	0.1018	0.0395
lszy	-0.0818	-0.0082	0.0011	0.0014	0.0100	0.1000	0.0215
dcyy	-0.0645	-0.0159	-0.0042	-0.0013	0.0093	0.0997	0.0252

khyy	-0.0752	-0.0104	0.0006	0.0009	0.0122	0.0998	0.0239
lbdq	-0.0801	-0.0169	-0.0033	-0.0006	0.0129	0.1001	0.0268
zjmd	-0.0781	-0.0117	-0.0019	-0.0010	0.0085	0.1000	0.0200
xbgf	-0.0909	-0.0224	-0.0034	-0.0025	0.0132	0.1002	0.0329
rf(%)	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0000

The summary statistics included the minimum, 1st quartile, median, mean, 3rd quartile, maximum and standard deviation (Std Dev). It could be seen that, in terms of risky stocks, the mean returns ranged between -0.2511% and 0.2202% and their standard deviations were from 0.019995 to 0.039468. The renewable energy industry had the highest expected return, while the household appliance industry was the least profitable. In addition, the home appliance industry had the largest volatility, followed by the pharmaceutical industry. However, the return rate of the risk-free asset remained constant (0.0041%) over the research period, and thereby its standard deviation was zero, indicating that there was no volatility.

3. Results And Discussion

3.1 Optimal Risky Portfolios

The empirical analysis was begun by running R across the whole sample period. In each concerned industry, it employed w_1 and w_2 which were both restricted to between -5 and 6 to describe the positions of two risky assets. The proportion of the other benchmark stock in the same industry was supposed to be 1-w_1-w_2, ensuring that the total position of the portfolio was equal to 1. Furthermore, each coefficient had 250 possible values, and positive values meant purchasing whereas negative coefficients implied short selling. With the assistance of double-for-loops, all potential investment portfolios based on w_1 and w_2 were constructed efficiently. By putting the mean-variance model into practice, portfolios with minimum standard deviations at every unique expected return were identified and jointly formed a parabola. The upper branch of the parabola consisted of investments which have higher average returns than the portfolio with the minimum volatility among all possible portfolios. Such curve was also called efficient frontier. In order to find out the optimal risky portfolio, the research then implemented the equation of Sharpe ratio. Since it was a widely held view that Sharpe ratio reflected asset's performance per unit of risk, the investment with the highest Sharpe ratio was defined as the market portfolio.

Figures 1-3 illustrated the investment opportunity sets with the selected stocks in the new energy, pharmaceutical and home appliance industries, respectively. The yellow curves referred to efficient frontiers, while the red points represented market portfolios in these three industries. Graphically, Sharpe ratio is exactly the slope of the line passing through both a risky portfolio and the risky-free asset.

Through the methodologies mentioned above, the study obtained that the optimal risky portfolio of the new energy industry was:

0.3453815×tsfn+0.3453815×sygf +0.3092369×akkj That of the medical industry was:

1.8915663×lszy-1.7309237×dcyy+0.8393574×khyy.

For the home appliance industry, the market portfolio was:

6.000000×lbdq+3.658635×zjmd-8.658635×xbgf

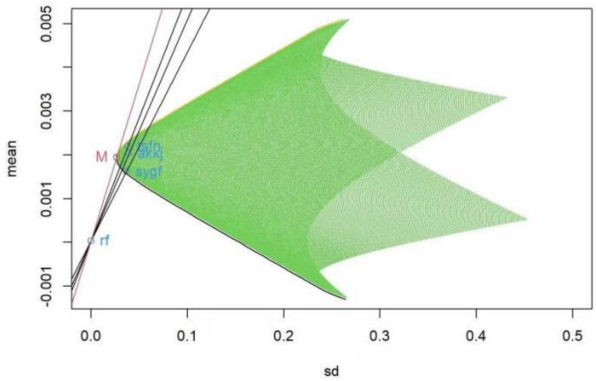

Figure 1 Investment opportunity set with three stocks in the new energy industry

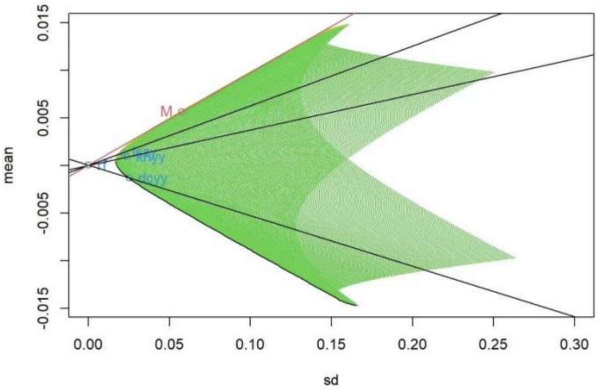

Figure 2 Investment opportunity set with three stocks in the pharmaceutical industry

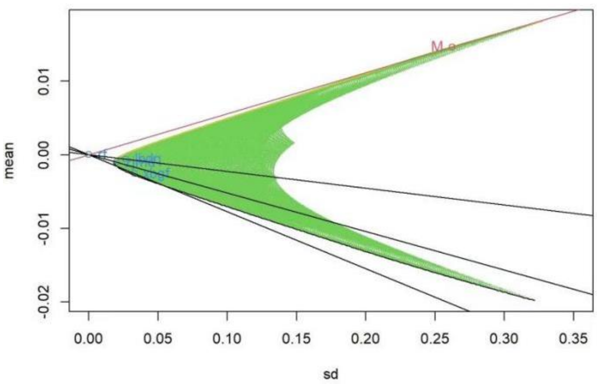

Figure 3 Investment opportunity set with three stocks in the home appliance industry

3.2 Statistics of Market Portfolios

According to Table 3, there was little difference in mean returns between the market portfolio and the individual stocks in the new energy industry. Stocks' coefficients indicated that they were weighted almost equally in the market portfolio. However, for the pharmaceutical and home appliance industries, investing in well-diversified portfolios could significantly improve the expected returns. In terms of volatility, the standard deviation of investment decreased by combining the benchmark assets in the new energy industry. By comparison, the market portfolio of the pharmaceutical and home appliance industries had the highest standard deviations among all chosen assets in the corresponding industries.

It is worth mentioning that optimal portfolio refers to the portfolio that pays the most per unit of risk in the market instead of the portfolio simply with maximum return or with minimum variance. For example, high returns are always accompanied by high risks, whereas blindly pursuing low risks may lose potential income. To be specific, all these three market portfolios had higher Sharpe ratios than any benchmark stocks in their respective industries, as shown in Table 3. That is, they greatly ensured relatively high expected returns while maintaining low risks.

Table 3. Summary statistics of assets

Asset	Mean	Std Dev	Sharpe Ratio
New energy industry			
tsfn	0.0022	0.0383	0.0565
sygf	0.0016	0.0367	0.0431
akkj	0.0020	0.0395	0.0506
market portfolio	0.0020	0.0266	0.0718
Pharmaceutical industry			
lszy	0.0014	0.0215	0.0626
dcyy	-0.0013	0.0252	-0.0530
khyy	0.0009	0.0239	0.0373
market portfolio	0.0057	0.0575	0.0976
Home appliance industry			
lbdq	-0.0006	0.0268	-0.0228
zjmd	-0.0010	0.0200	-0.0523
xbgf	-0.0025	0.0329	-0.0775
market portfolio	0.0147	0.2624	0.0557

3.3 *Comparison in different industries*

Optimization effects perform differently in diverse industries. Therefore, market portfolios in each industry should be evaluated separately. For the new energy industry, the Sharpe ratio of its optimal investment portfolio strategy increased by 27.14%, 66.48% and 41.80%, compared with those of *tsfn*, *sygf* and *akkj*. In the field of pharmaceuticals, the performance of the market portfolio by adjusting for the volatility was better than its component stocks, with 55.94%, 284.00% and 161.85% respectively. Moreover, investing in the market portfolio of the home appliance industry produced a 344.52% improvement in risk-adjusted return of *lbdq*, a 206.61% increase in risk-adjusted return of *zjmd* and a 171.84% raise in risk-adjusted return of *xbgf*. Namely, optimization effects were most significantly in the home appliance industry but not quite considerable in the new energy industry. The optimization benefits in the medical industry just stood at an intermediate position among the three industries.

Two important factors associated with optimization effects are diversification benefits and leverage [9]. Vannoorenbergh et al. [10] state that large-scale industries generally have an advantage in reducing volatility. As a traditional industry, the scale of the home appliance industry was massive and thus it could diversify risks efficiently [11], while the small-scale new energy industry did not have significant diversification benefits since it was an emerging industry [12]. Furthermore, the standard deviation of portfolio return is a function of the correlations of securities in the portfolio. Figure A3 showed that the benchmark assets in the home appliance industry had stronger positive correlations with each other than those in the other two industries. As a result, investors could protect the principal successfully by short selling several stocks in the home appliance industry. Such method is also commonly known as leverage, which can magnify the results of investments. The market portfolio in the home appliance industry borrowed capital by short selling 8.658635 shares of *xbgf*. Its high leverage expanded the asset base and generated more incomes on risk capital. Consequently, the optimal portfolio in the household appliance industry created the most substantially increases in the Sharpe ratio. Likewise, it can be confirmed that the market portfolio's improvement in the Sharpe ratio was less remarkable in the renewable and sustainable energy industry than in the pharmaceutical industry. These findings may be the reason why the home appliance industry had the most optimization benefits but the optimization effects in the new energy industry were the most insignificant.

4. Conclusion

Portfolio construction was an important way to protect principals and simultaneously take advantage of changes in interest rates. This research combined the mean-variance model with Sharpe ratio to explore the optimal risky investment strategies in the renewable energy, pharmaceutical and household appliance industries.

There were two key findings from the paper. Firstly, investing in the market portfolio could earn more profits per unit of risk than the benchmark stocks in each industry. In addition, the ray connecting the optimal risky portfolio and the risk-free asset was well known as the capital market line (CML), and market portfolio was precisely the tangent point between efficient frontier and CML. All portfolios on CML shared the highest Sharpe ratio and were equivalent in a trade-off between expected return and risk. Therefore, rational investors with mean variance preference should select portfolios from CML. The market portfolios established in the study provided participants with a direction to invest efficiently. Secondly, the optimization effects in the home appliance industry were the most significant, while that in the new energy industry was not very considerable. The main reason was that diversification and leverage effects might be more substantial in the home appliance industry due to its massive scale and the high correlations in its benchmark stocks. This outcome helped people further understand the essence of optimization benefits as well as the differences between industries. However, the study also had some limitations. First, the inferences about why optimization benefits varied in different industries were merely on the ground of previous literature and lacked statistic evidence. More relative empirical research was required. Second, although the traditional Sharpe ratio calculation method was simple and easy to understand, it had a large number of defects and restrictions in practice. As a result, the structured Sharpe ratio in the sense of Value at Risk (VaR) and Conditional Value at Risk (CVaR) might be more proper for seeking optimal risky portfolios. Third, the paper focused on the single-industry market portfolios and there were only three benchmark stocks in each industry. Similar analysis could be extended to further discussions about the construction of multi-industries market portfolios based on more stocks.

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APPENDIX

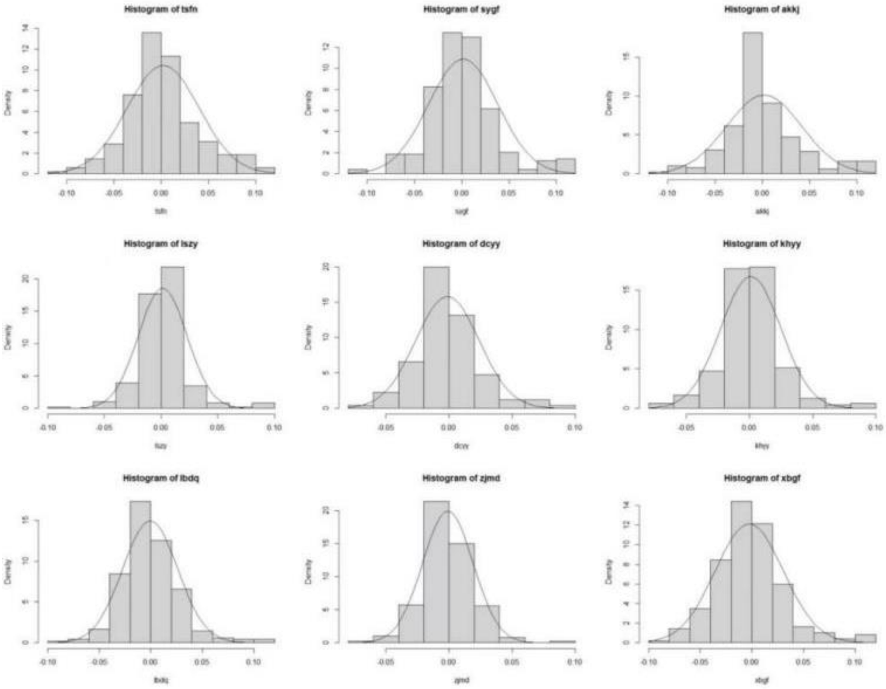

Figure A1 Histograms and estimated possibility density functions of 9 risky stocks' returns