# Fundamental Multi-Factor Stock Selection Strategy Research - Taking the Constituents of the Shanghai and Shenzhen 300 Index as an Example

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**Abstract.** The most important aspect of stock investment is the ability to select good stocks, which can bring investors good excess returns before the market becomes strong and efficient. With the rapid development of computer technology and big data application, the multi-factor stock selection theory in quantitative investment is becoming increasingly sophisticated, and has become a popular and stable stock selection method. Based on the "RiceQuant" quantitative investment analysis platform, this study adjusts the parameters of the profitability factors (return on net assets and gross profit margin) in the fundamental multi-factor stock selection model using data from the constituents of the Shanghai and Shenzhen 300 Index from 2017 to 2020, selects the optimal parameters based on backtesting returns and risk screening, and further optimizes the model by including both profitability factors. These results reflect the screening ability of different profitability factors for stocks and can provide reference for the strategy design of multi-factor models.

**Keywords:** Stock Market; Fundamental Indicators; Multi-Factor Model.

## 1. Introduction

With the improvement of China's stock market system and the increase in disposable income of residents, various market participants have put forward higher requirements for investment returns. Choosing valuable stocks for investment in a complex market has become an increasingly important focus. The multi-factor model is one of the most widely used models in the stock selection field. The multi-factor stock selection model is based on theoretical foundations such as the capital asset pricing model (CAPM), arbitrage pricing theory (APT), Fama-French three-factor and five-factor models [1]. The CAPM model proposes a linear relationship between the security return and the market portfolio return, which is expressed in a single-factor model. The APT theory extends the single-factor model to a multi-factor model. The subsequent Fama-French three-factor, five-factor models, etc. began to try to find specific factors related to security returns in the market. The current multi-factor stock selection model is developed based on this.

Among them, the fundamental factor is an important stock selection factor, which includes the macro level, industry mid-level, and micro level of the enterprise. This article will focus on the micro level of the enterprise, taking the enterprise itself as the research object, and mainly using financial analysis to estimate the long-term trend of the company's stock in the future. The common categories of fundamental factors at the micro level of the enterprise include profitability factors, operating capacity factors, cash flow factors, capital structure factors, debt-paying capacity factors, valuation factors, growth factors, etc.

## 2. Literature Review

In recent years, research on stock selection using fundamental multi-factor models has been widely conducted. Guo and Yang explored the relationship between financial factors and stock prices of companies in the SSE 180 Index, and used financial factors to predict stock price trends [2]. Albadvi et al. studied the impact of both fundamental and industry factors on stock price movements and found that these two types of factors have a significant influence [3]. Fan et al. used dynamic regression analysis to study stock trading strategies based on multi-factor models [4]. Fei and Cai compared domestic and foreign multi-factor models in the stock market and proposed a multi-factor model based on market factors, value factors, quality factors, growth factors, and liquidity factors. They used this model for stock selection and obtained some effective stock portfolios [5]. Ahn and Horenstein believed that companies with good fundamental data would have better long-term stock performance [6]. Chen et al. compared the effectiveness of multiple factors such as market, value, growth, quality, leverage, and liquidity, and constructed a stock selection strategy based on multi-factor models using factor analysis and dynamic weighted regression methods [7]. Tandon and Leclercq used machine learning methods to discover nonlinear relationships among multiple factors, improving their predictive ability and investment returns [8]. Hu et al. optimized the traditional five-factor model by constructing an accounting information relevance index from the perspective of the enterprise [9]. Hou and Wang believed that fundamental analysis is an important theoretical basis for finding alpha factors, and provided a detailed summary and outlook of the current development of fundamental quantitative investment [10].

## 3. Data Source and Method

### 3.1 Sample Selection and Data Source

This article uses the constituents of the CSI 300 Index as the asset pool and selects daily data from January 1, 2017 to August 1, 2020 as the sample period. The data source is a third-party quantitative backtesting platform called Ricequant. Ricequant currently provides investment research, strategy backtesting, and real-time simulation trading functions. Its research platform, based on IPython Notebook, introduces the financial data module RQdata, which can efficiently provide users with high-quality historical and real-time volume and price data, including stocks, funds, convertible bonds, options, indexes and other multi-asset data. The asset backtesting framework currently offers two options: stocks and futures. In addition, the platform provides clear and complete documentation on RQData usage and quantitative platform, which is easy to use and convenient.

### 3.2 Factor Selection

Referring to existing studies [11-14], the equity multiplier, return on net assets, price-to-book ratio, gross profit margin, and total profit (year-on-year growth rate) are selected as fundamental factors in the multi-factor model. Among them, the equity multiplier is a solvency factor calculated as total assets/total equity; the price-to-book ratio is a valuation factor calculated as market price per share/book value per share; the total profit (year-on-year growth rate) is a growth factor calculated as the annual profit growth amount/last year's total profit×100%; return on net assets and gross profit margin are profitability factors, where return on net assets=net profit/average net assets×100%, and gross profit margin=(net sales revenue-product costs)/net sales revenue×100%. This study mainly adjusts the range of profitability factors in the screening and selection strategy.

This article uses the scoring method for constructing the multi-factor stock selection model, which can effectively avoid the impact of inconsistent units and extreme values of various indicators. The scoring method ranks stocks based on the size of each factor, assigns scores based on the stock's ranking, and finally adds up the scores for each stock on different factors based on the specified factor weights. The high-scoring stocks are selected to construct the investment portfolio based on the total scores of each stock on all factors. Given the relative stability, simplicity and convenience of the equal-weight scoring method, it performs well in backtesting. Therefore, this article uses the equal-weight scoring method to construct the multi-factor stock selection model.

# 4. Results and discussion

## 4.1 Adjustment of Net Asset Return

Using the constituents of the CSI 300 Index as the full sample (including ST stocks), the model selects the equity multiplier, return on net assets, price-to-book ratio, and total profit (year-on-year growth rate) as factors. The maximum number of stocks held is 20, and the portfolio is rebalanced every 5 trading days. The default tax and fee settings in the ricequant platform are used, and the initial investment amount is 1 million RMB. The benchmark return is the annualized return of the CSI 300 Index. The stock selection criteria are equity multiplier less than 3, price-to-book ratio greater than 0, and total profit (year-on-year growth rate) greater than 30%. The return on net assets parameter is adjusted, and the results are shown in Table 1.

**Table 1.** Comparison of backtesting results for different ranges of net asset return

| Evaluating indicator | net assets return | | | |
|---|---|---|---|---|
| | ＞5% | ＞10% | ＞20% | ＞30% |
| Backtesting Return | 49.54% | 82.73% | -2.64% | 122.01% |
| Annual Backtesting Return | 12.35% | 19.06% | -0.77% | 25.96% |
| Benchmark Backtesting Return | 41.84% | 41.84% | 41.84% | 41.84% |
| Annual Benchmark Backtesting Return | 10.64% | 10.64% | 10.64% | 10.64% |
| Alpha | 0.0149 | 0.0816 | -0.1051 | 0.184 |
| Beta | 1.027 | 1.0321 | 0.8847 | 0.605 |
| Sharp Ratio | 0.5023 | 0.6923 | -0.0047 | 0.9553 |
| Sortino Ratio | 0.6899 | 0.9569 | -0.0064 | 1.4212 |
| Information ratio | 0.1294 | 0.4861 | -0.5191 | 0.9172 |
| Annualized volatility | 0.2284 | 0.2611 | 0.2613 | 0.2434 |
| Maximum Drawdown | 36.35% | 44.35% | 50.84% | 25.35% |
| Annualized tracking error | 0.1097 | 0.1662 | 0.1975 | 0.2263 |
| Annualized downward volatility | 0.1663 | 0.1889 | 0.1923 | 0.1636 |

From the perspective of backtesting returns, the highest returns were achieved when the net return on assets was greater than 30%, followed by those greater than 10%. In terms of risk-adjusted returns, the strategy with net return on assets greater than 30% had the highest Sharpe ratio of 0.96, with relatively high Sortino and Information ratios, and offered more considerable returns for a given level of risk compared to other strategies. In terms of risk, the maximum drawdown of the strategy with net return on assets greater than 30% was 25.35%, which was lower than that of other groups. When the net return on assets greater than 30% was used as a selection criterion, the backtesting results were the best, as shown in Figure 1.

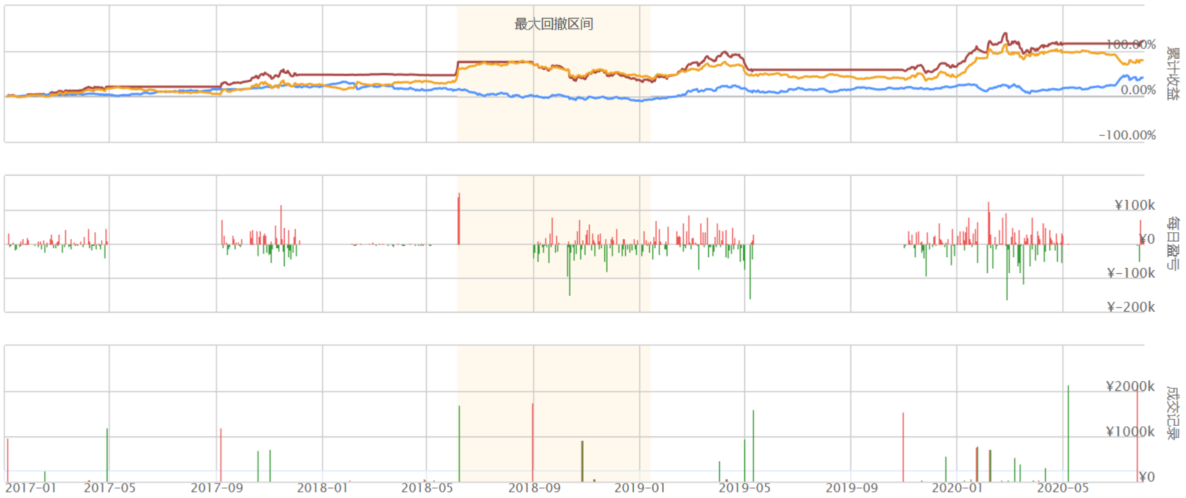


**Figure 1.** Optimal backtesting results with adjusted net asset return

### 4.2 Adjustment of Gross Profit Margin

Using the constituent stocks of the Shanghai and Shenzhen 300 Index (including ST stocks), the equity multiplier, gross profit margin, price-to-book ratio, and total profit (year-on-year growth rate) were selected as the model inputs. The maximum number of holdings is 20 stocks, and the portfolio is rebalanced every 5 trading days. The default tax and fee settings in the Ricequant platform are used, and the initial investment amount is 1 million yuan. The benchmark return is the annualized return of the Shanghai and Shenzhen 300 Index. The stock selection criteria are: equity multiplier less than 3, price-to-book ratio greater than 0, and total profit (year-on-year growth rate) greater than 30%. The gross profit margin parameter is adjusted and the results are shown in Table 2.

**Table 2.** Comparison of backtesting results for different ranges of gross profit margin

| Evaluating indicator | gross profit margin | | | |
|---|---|---|---|---|
| | ＞5% | ＞10% | ＞20% | ＞30% |
| Backtesting Return | 79.28% | 76.69% | 77.18% | 90.72% |
| Annual Backtesting Return | 18.40% | 17.90% | 18.00% | 20.54% |
| Benchmark Backtesting Return | 41.84% | 41.84% | 41.84% | 41.84% |
| Annual Benchmark Backtesting Return | 10.64% | 10.64% | 10.64% | 10.64% |
| Alpha | 0.0768 | 0.0718 | 0.0712 | 0.0939 |
| Beta | 1.0098 | 1.0107 | 1.0303 | 1.065 |
| Sharp Ratio | 0.75 | 0.731 | 0.7221 | 0.7912 |
| Sortino Ratio | 1.0252 | 1.003 | 0.9952 | 1.0952 |
| Information ratio | 0.771 | 0.7232 | 0.6795 | 0.8187 |
| Annualized volatility | 0.2207 | 0.2206 | 0.2262 | 0.2363 |
| Maximum Drawdown | 31.47% | 32.48% | 34.12% | 34.72% |
| Annualized tracking error | 0.0993 | 0.0988 | 0.1037 | 0.1131 |
| Annualized downward volatility | 0.1614 | 0.1608 | 0.1641 | 0.1707 |

Based on the backtesting results, when the sales gross profit margin is higher than 30%, the return is slightly higher than other groups. Looking at risk-adjusted returns, the strategy with a sales gross profit margin of over 30% has the highest Sharpe ratio of 0.79, with Sortino ratio and information ratio relatively high, making it more attractive in terms of unit risk returns compared to other strategies. In terms of risk, the maximum drawdown of the strategy with a sales gross profit margin over 5% is 31.47%, which is lower than other groups. When the sales gross profit margin is used as a selection criterion, a strategy with a sales gross profit margin of over 30% shows the best backtesting results, as shown in Figure 2.

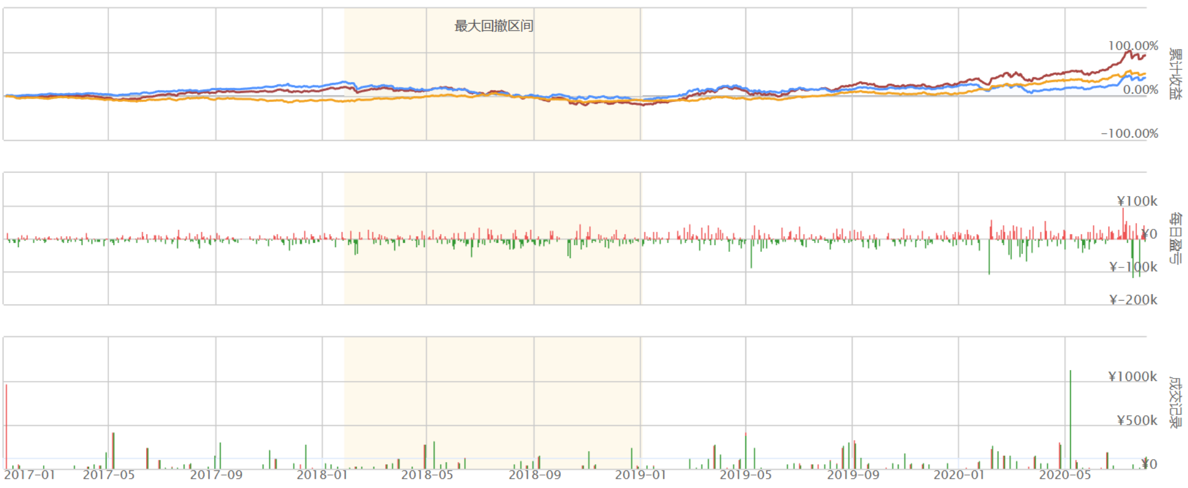


**Figure 2.** Optimal backtesting results with adjusted gross profit margin

### 4.3 Combination of Net Asset Return and Gross Profit Margin

Based on a multi-factor model that includes equity multiplier, net asset return rate, price-to-book ratio, sales gross margin rate, and profit total amount (year-on-year growth rate), stocks were selected based on the criteria that equity multiplier is less than 3, price-to-book ratio is greater than 0, and profit total amount (year-on-year growth rate) is greater than 30%. Based on the optimal parameters selected in the previous section, i.e., net asset return rate greater than 30% and sales gross margin rate greater than 30%, the backtesting result is shown in Figure 3. The backtesting return is 171.91%, and the annualized return is 33.56%, which is higher than the return obtained by only using net asset return rate and sales gross margin rate as stock selection factors. From the perspective of risk-adjusted return, the Sharpe ratio for the combined factors is 1.16, which is lower than the strategy using only net asset return rate as the stock selection factor. From a risk perspective, the maximum drawdown using the combined factors is 25.33%, which is lower than the strategy using only sales gross margin rate as the stock selection factor, and is similar to the strategy using only net asset return rate as the stock selection factor in terms of risk.

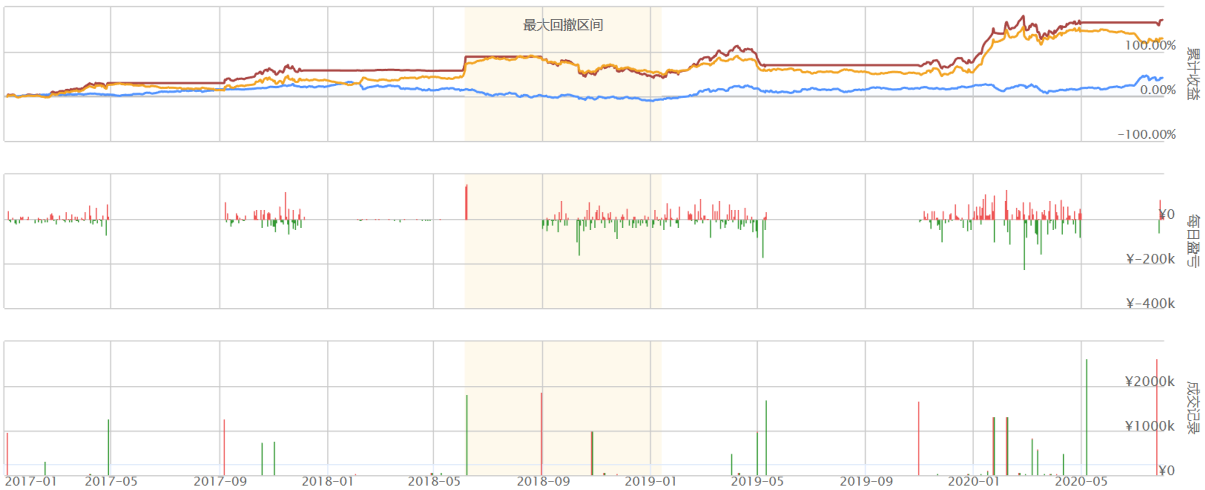


**Figure 3.** Optimal backtesting results with combination factors.

## 5. Conclusion

When using a single profitability factor for stock selection, the optimal range for net asset return rate is greater than 30%, and the optimal range for sales gross profit rate is also greater than 30%. When using net asset return rate and sales gross profit rate as profitability factors and selecting stocks based on the optimal ranges obtained from single factor testing, the backtesting returns are significantly better than using a single factor, but the risk-adjusted returns are lower, and the risk is similar to that of the strategy using only net asset return rate as a selection factor. The research results in this article reflect the screening ability of different profitability factors for stocks, and can also provide reference for the strategy design of multi-factor models.

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