Construction and Validation of Industry Prosperity Model in the Chinese Stock Market

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Abstract. Within the intricate and ever-evolving tapestry of China's equity market, the discernment of high-potential listed entities remains a linchpin for investors in their quest for superlative returns. This study reconstructs an industry prosperity model and explores the correlation between industry prosperity and returns, aimed at enhancing the efficiency of investment returns. Selecting the Chinese stock market as the study platform, this study meticulously develops an industry rotation investment model based on industry prosperity. Experimental results confirm the effectiveness of the constructed prosperity model in identifying efficient industries and grasping market trends, significantly enhancing investor returns. This study not only provides profound theoretical insights but also, through empirical studies, deepens the understanding of industry dynamics in the Chinese stock market, offering valuable guidance for optimizing investment portfolio strategies.

Keywords: Industry Prosperity, Industry Rotation, Correlation, Chinese Stock Market

1 Introduction

In the current era marked by rapid advancements in information technology, financial markets have grown increasingly complex, posing substantial challenges for investment decision-making. Within this intricate landscape, the accelerated growth of China's economy has catapulted the Chinese stock market into the global spotlight. Distinguished by its unique characteristics, this market presents both distinct challenges and opportunities for investors. Notably, industry rotation in the Chinese stock market, driven by specific market traits and inherent investment values, has garnered significant attention from both academic scholars and investment professionals.

This study develops an industry rotation model by integrating macroeconomic indicators, comprehensive industry analysis, and analysts' predictions into a novel industry prosperity index. This model effectively monitors industry prosperity trends, capturing leading market sectors with precision and facilitating the generation of significant excess returns. It offers an innovative perspective for constructing industry rotation strategies, enhancing investor returns and serving as a theoretical and empirical beacon for financial market researchers.

The article is meticulously structured: Following this introduction, the second section provides a detailed literature review, laying the theoretical foundation for the research. The third section

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describes the research methodology and the construction of the model. The fourth section discusses the results of the empirical analysis. The concluding section, the fifth, reflects on the theoretical and practical implications of the research findings.

2 Literature Review

Xiaoguang Lu and Yingli Shen [1] probed into the effects of sector rotation, uncovering significant variances in sectoral performance across economic cycles. Chisholm, O'Reilly, and Betro [2] championed the efficacy of a sector-based investment framework in portfolio architecture. Chava, Hsu, and Zeng [3] delved into the symbiosis between historical business cycles and sector returns. Sassetti and Tani [4], employing market timing techniques, validated that investment strategies premised on sector return path dependency consistently eclipse traditional buy-and-hold strategies. Sarwar, Mateus, and Todorovic [5] scrutinized the risk-adjusted performance of sector investment portfolios and sector rotation strategies in the U.S. market, leveraging the Fama-French five-factor model. Wang, Zhang, and Chen [6] utilized the Lasso regression model to engineer a profitable sector rotation trading schema for the Chinese stock market. The advent of technological advancements and the proliferation of machine learning have imbued sector rotation strategies with significant enhancements. Molchanov and Stangl [7] challenged conventional notions of business cycle-based sector rotation strategies, demonstrating that sector performance is not systematically linked to business cycle stages.

Chen, Xie, and Zeng [8] harnessed Hidden Markov Models in analysing sector rotation in the stock market. Karatas and Hirsa [9] proffered an avant-garde sector rotation prediction method amalgamating machine learning and deep learning technologies. Su, Li, and Akter [10] exploited Vector Error Correction Models (VECM) to decipher the guiding interrelations between sectors in the Chinese stock market. Limongi Concetto and Ravazzolo [11] assessed the impact and predictive capacity of investor sentiment on stock returns, uncovering a significant negative correlation in the U.S. market, while in European markets, the predictive power of sentiment appeared more attenuated. Luo, Wu, Su, and Yu [12] identified a positive correlation between investor optimism about profits and short-term stock returns, indicating that heightened optimism precipitates elevated valuations in the short run. In the context of market analysts' roles, KADAN, MADUREIRA, WANG, and ZACH [13] probed the industry expertise of sell-side analysts, uncovering their significant acumen in cross-industry recommendations, which leads to abnormal returns, thereby underscoring the salience of expertise in investment decisions.

3 Theory

Industry prosperity is a composite indicator designed to reflect the market flourishing level of a specific sector. It is derived by weighting various industry-specific metrics, enabling the timely reflection of macroeconomic performance and the operational conditions of companies within the industry. Moreover, it can predict future economic trends and industry development to a certain extent. In this study, industry prosperity is calculated as a composite indicator by equally weighting five key metrics, representing the future growth trends of the industry.

Firstly, this study determines the institutional industry prosperity index by analyzing the proportion of institutions that have recently upgraded their industry ROE. This index reflects the market's optimism about the industry:

$$\boldsymbol{R_1} = \frac{\boldsymbol{Number\ of ROE_{up}}}{\boldsymbol{Number\ of\ ROE_{sum}}} * \mathbf{100\%} \quad (1)$$

Where:

$\boldsymbol{R_1}$ is the institutional industry prosperity index

$\boldsymbol{Number\ of\ ROE_{up}}$ is the total number of institutions that have upgraded industry ROE

$\boldsymbol{Number\ of\ ROE_{sum}}$ is the total number of institutions

Next, to measure the change in the proportion of institutions bullish on the industry ROE over the past year, we calculated the institutional industry prosperity index_zscore:

$$\boldsymbol{R_2} = \frac{\boldsymbol{R_1} - \boldsymbol{R_{1_{mean}}}}{\boldsymbol{R_{1_{std}}}} \quad (2)$$

Where:

$\boldsymbol{R_1}$ is the institutional industry prosperity index

$\boldsymbol{R_2}$ is the institutional industry prosperity index_zscore

$\boldsymbol{R_{1_{mean}}}$ is the average of the institutional industry prosperity index

$\boldsymbol{R_{1_{std}}}$ is the standard deviation of the institutional industry prosperity index

The Analyst Industry Prosperity Index is often seen as a representative of investor confidence. A high prosperity index means analysts are optimistic about the industry's prospects, which may attract more investment and boost the overall performance of the industry. This study argues that the analyst's forecast of a stock's net profit for the next year, FTTM, cannot be directly used, as its calculation formula might not be accurate enough at the beginning of the year when annual reports are not yet published.

Therefore, this study chooses to calculate the net profit for the next four quarters, FTTM, based on the already published quarterly financial reports. The new calculation formula is as follows:

$$\boldsymbol{P_{FTTM}} = \left(\boldsymbol{P_{FY_1}} - \boldsymbol{P_{report}}\right) + \boldsymbol{P_{FY_2}} * \frac{\boldsymbol{P_{report}}}{\boldsymbol{P_{FY_1}}} \quad (3)$$

Where:

$\boldsymbol{P_{FTTM}}$ is the analyst's forecast of the net profit for the next four quarters for individual stocks.

$\boldsymbol{P_{FY_1}}$ is the analyst's forecast of earnings for the first upcoming year for individual stocks.

$\boldsymbol{P_{FY_2}}$ is the analyst's forecast of earnings for the second upcoming year for individual stocks.

$\boldsymbol{P_{report}}$ is the actual reported net profit attributable to the parent company for the individual stock.

After obtaining the forecast of net profit for the next year for individual stocks, this study uses a bottom-up approach to calculate the analysts' overall industry ROE forecast:

$$ROE_{FTTM} = \frac{sum(P_{FTTM})}{sum(equity)} \quad (4)$$

Where:

ROE_{FTTM} is the analysts' forecast of ROE for the overall industry.

P_{FTTM} is the analysts' forecast of net profit for the next four quarters for individual stocks.

equity is the net asset value of the overall industry.

Upon receiving the analysts' forecasts for the Return on Equity (ROE) for the upcoming year, our initial challenge lies in synthesizing these individual projections to form a comprehensive estimate of future industry ROE. An examination of nearly a hundred research reports published by various research institutions revealed significant disparities in both the scope and depth of these analyses. Given the diversity in resource allocation and investment research capabilities of these institutions, this study posits that the traditional equal-weighting approach may lack precision in aggregating analyst forecasts.

Therefore, this study introduces a weighted methodology based on historical forecast accuracy. This approach evaluates the precision of an analyst's historical forecasts as a key indicator of their respective institution's overall forecasting ability. Within the framework of existing financial forecasting research, this methodology offers a more refined assessment of analyst forecasting capabilities.

Further research indicates that analysts with a history of high accuracy in their forecasts are likely to maintain this precision in future earnings predictions. This finding aligns with the existing literature regarding the impact of an analyst's expertise and experience on forecast performance. Theoretically and methodologically, assigning greater weight to these historically high-performing analysts demonstrates innovation.

To quantitatively assess the accuracy of analyst forecasts, this study employed the Absolute Forecast Error (AFE) method. This approach calculates the absolute difference between forecasted and actual reported values and normalizes it against the actual reported values, providing an intuitive metric for comparing the precision of different analysts' forecasts. AFE is widely utilized in the academic field of financial forecasting, and its effectiveness has been validated and recognized in numerous studies.

$$PA = \left| \frac{Profit_{FY1} - Profit_{report}}{abs(Profit_{report})} \right| \quad (5)$$

Where:

PA stands for predictive accuracy

P_{FY_1} is the analyst's forecast of earnings for the first upcoming year for individual stocks.

P_{report} is the actual reported net profit attributable to the parent company for the individual stock.

Guided by the proposed formula, we initially conducted an exhaustive statistical analysis of the forecasting accuracy of all analysts over the past three years. Utilizing this data, we implemented an innovative scoring method, which employs the analysts' forecast accuracy as the basis for weighting. This approach not only considers the historical performance of each analyst but also provides a quantified evaluation framework for the precision of future forecasts.

Subsequently, we calculated the relative importance of each analyst in forecasting the Return on Equity (ROE) for the upcoming year, based on their weighted scores. The crux of this methodology lies in translating the historical forecast accuracy of analysts into weights for their future predictions. This process amalgamates all analysts' forecasts, thereby forming a holistic projection of the industry's ROE for the following year.

After obtaining the analysts' forecast of overall industry ROE, this paper calculates the current forecast of ROE_FTTM for the next four quarters and then computes the z-score of this indicator over the past year as a measure of the current analysts' forecast of the industry ROE for the upcoming year (ROE prediction value_zscore).

This paper also extracts data on all component stocks in the industry, such as net profit growth rate, and IROE, and averages them equally. Then, it ranks the industry's net profit growth rate, and IROE changes to obtain the industry's historical prosperity index.

$$\boldsymbol{GROI} = \frac{\boldsymbol{ISOIGR_i}}{\boldsymbol{N}} \tag{6}$$

$$\boldsymbol{IROE} = \frac{\boldsymbol{ROE_i}}{\boldsymbol{N}} \tag{7}$$

Where:

$\boldsymbol{GROI}$ is the net profit growth rate for the industry as a whole

$\boldsymbol{N}$ is the number of stocks in the industry

$\boldsymbol{ISOIGR_i}$ is the net profit growth rate of the ith stock in the industry

$\boldsymbol{ROE_i}$ is the past year's ROE for the ith stock in the industry

$\boldsymbol{IROE}$ is the industry's roe for the past year

In this study, we first utilized formulas for the industry's net profit growth rate and the Return on Equity (ROE) to systematically analyse the Growth Return on Investment (GROI) and Industry Return on Equity (IROE) across different sectors. These two metrics are integral in evaluating the performance of an industry.

To further delve into the historical prosperity of industries, we introduced a scoring-based approach. This method is designed to convert GROI and IROE into a comprehensive score of prosperity, thus providing a quantitative assessment of the industry's past performance.

$$\boldsymbol{R_4} = \boldsymbol{rank}(\boldsymbol{GROI}) + \boldsymbol{rank}(\boldsymbol{IROE}) \tag{8}$$

Where:

$\boldsymbol{GROI}$ is the net profit growth rate for the industry as a whole

$\boldsymbol{IROE}$ is the industry's roe for the past year

$\boldsymbol{R_4}$ is the historical industry prosperity.

The information ratio refers to the ratio of an industry's market value to its related information quantity, reflecting the degree of information asymmetry in an industry. It is used to measure the performance of an investment portfolio, showing the relationship between the portfolio's excess return and active risk. The following formula is proposed in this study to calculate the industry's information ratio:

$$\boldsymbol{IR_{industry}} = \frac{\boldsymbol{Mean(ANER)}}{\boldsymbol{Std(ANER)}} \tag{9}$$

$$\boldsymbol{IR_{mean}} = \frac{\sum \boldsymbol{IR_{industry}}}{\boldsymbol{29}} \tag{10}$$

$$\boldsymbol{R_5} = \frac{\boldsymbol{IR_{industry}}}{\boldsymbol{IR_{mean}}} \tag{11}$$

Where:

$\boldsymbol{R_5}$ is the industry's relative information ratio.

$\boldsymbol{IR_{industry}}$ is the industry information ratio.

$\boldsymbol{IR_{mean}}$ is the industry's equal-weighted information ratio.

$\boldsymbol{ANER}$ is average annualised excess returns

Finally, by comprehensively considering the institutional industry prosperity index, institutional industry prosperity z-score, analysts' forecast z-score for the industry ROE in the coming year, historical industry prosperity, and the industry's relative information ratio, this study constructs the Industry Prosperity (IP):

$$\boldsymbol{IP = Rank(R_1) + Rank(R_2) + Rank(R_3) + Rank(R_4) + Rank(R_5)} \tag{12}$$

Where:

$\boldsymbol{R_1}$ is the institutional industry prosperity index.

$\boldsymbol{R_2}$ is the institutional industry prosperity z-score.

$\boldsymbol{R_3}$ is the analysts' forecast z-score for the industry ROE in the coming year.

$\boldsymbol{R_4}$ is the historical industry prosperity.

$\boldsymbol{R_5}$ is the industry's relative information ratio.

4 Experiments

4.1 Data source

In this study, the Wind database was the primary source of detailed financial and market data, including analysts' earnings forecasts for individual stocks, consensus figures, and transaction data. This information supported a bottom-up approach to estimate institutional earnings expectations across sectors, evaluating forecast accuracy through consensus figures.

For strategy verification, the Join Quant platform served as the main analytical tool, processing data on monthly industry returns, daily stock returns, and closing prices. This approach provided a thorough and comprehensive market context, bolstering the empirical validity and applicability of our findings.

4.2 Industry Prosperity and Returns

This study investigates the relationships between industry prosperity and monthly industry returns by analysing data from the Chinese stock market from February 28, 2013, to May 31, 2022. Advanced statistical methods were applied to explore the linkage between industry prosperity and aggregate monthly returns. To clearly present our findings, a heatmap was used to visually represent the correlation intensities among different industries, illustrating the connection between their prosperity and monthly return fluctuations (see Fig.1).

The colour gradations in the heatmap intuitively indicate correlation strengths, providing a detailed and nuanced analysis.

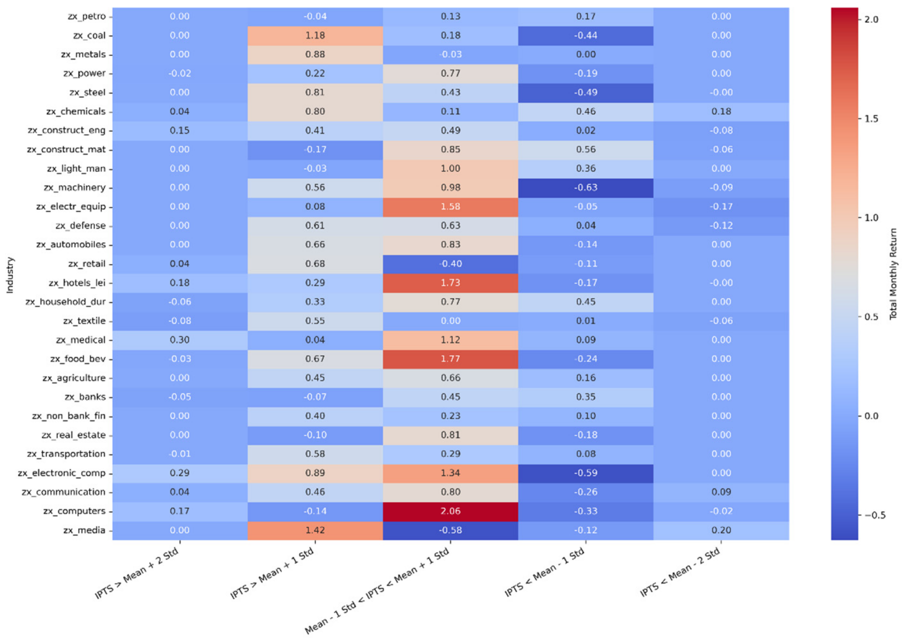

Fig.1 Relationship between IP and industry returns

This study investigates the fluctuations in the Industry Price to Sales (IP) ratio and its correlation with industry returns. As shown in Fig. 1, the data reveals that IP values for most industries typically oscillate within ±1 standard deviation from their mean. However, some sectors display anomalous IP values exceeding this range, which are often associated with significant market outcomes. For example, sectors like "zx_media," "zx_coal," and "zx_electronic_comp" registered returns of 142%, 118%, and 89% respectively when their IP exceeded the mean plus one standard deviation, indicative of strong market performance. Conversely, sectors like "zx_real_estate," "zx_computers," and "zx_banks" experienced modest negative returns under similar conditions.

When the IP falls below the mean minus one standard deviation, most sectors typically show negative returns. Specifically, sectors such as "zx_coal", "zx_steel", "zx_machinery", and "zx_electronic_comp" faced losses of 44%, 49%, 63%, and 59% respectively, illustrating a negative correlation between reduced IP values and sector performance.

The study also examines the correlation between industry prosperity and monthly industry returns. A pattern emerges from the heatmap analysis: sectors with IP values significantly above the mean tend to show positive monthly returns, whereas those significantly below the mean often exhibit negative returns. This suggests a strong correlation between industry prosperity and monthly industry performance.

In summary, this research posits that high prosperity levels within an industry are likely to correlate with positive monthly returns, while lower prosperity levels tend to correlate with negative returns. A comprehensive table correlating the prosperity of all industries with their monthly returns was compiled to further validate this hypothesis and enhance understanding of the impact of industry prosperity on stock market returns.

Tab.1 Distribution of IP in relation to industry returns

Condition	Average total monthly return
IP>mean+2std	7.388%
IP>mean+1std	44.36%
Mean+1std>IP>mean-1std	67.86%
IP<mean-1std	-4.034%
IP<mean-2td	-3.5%

This meticulous analysis of the data has revealed a notable trend: industries with an Industry Price to Sales (IP) ratio exceeding the mean plus one standard deviation (IP > mean + 1std) average a return rate of 44.36%. Conversely, when the IP ratio falls below the mean minus one standard deviation (IP < mean - 1std), the return rate becomes negative, averaging -4.034% (see Tab. 1).

These findings underscore a significant positive correlation between industry prosperity and monthly total returns, suggesting that selecting industries with higher prosperity levels can potentially enhance returns and reduce investment risks.

Building on this, the study proposes an investment strategy based on selecting the top five industries by IP ranking each cycle to optimize returns. This strategy was empirically tested by comparing these industries against those ranked sixth to twenty-ninth, using equal-weighted monthly return rates over time. The results, detailed in charts in subsequent sections, visually demonstrate the superior performance of higher IP-ranked industry groups, reinforcing the practical utility of this strategy for investment portfolio optimization and risk mitigation.

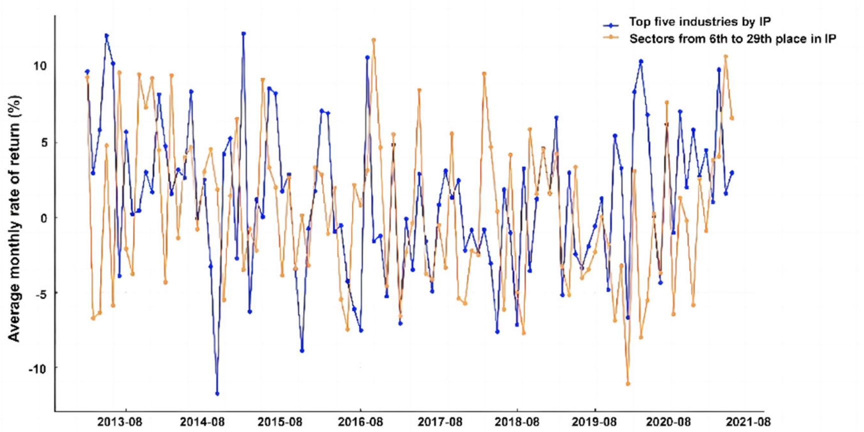

Fig.2 Monthly Returns of the Top 5 IP Ranking Sectors vs. the Remaining Sectors in Their Respective Sectors

The detailed analysis of the charts drawn in this study reveals a consistent pattern: The results, detailed in Fig. 2, in the majority of time periods, the top five industries ranked by IP exhibit higher equal-weighted monthly return rates compared to those ranked sixth to twenty-ninth. Moreover, the top five IP-ranked industries mostly maintain positive equal-weighted monthly returns during most periods. This finding suggests that incorporating the top five IP-ranked industries into the decision logic for constructing an industry rotation model can not only effectively enhance returns but also help in reducing investment risks.

Based on this insight, we propose a construction approach for an industry rotation model. The core of this model lies in identifying and utilizing the changes in industry prosperity, thereby choosing the most promising industries for investment at different times. Through this method, we can not only respond more flexibly to market fluctuations but also seek to maximize investment returns under the premise of controllable risks.

4.3 The Construction and Optimization of the Industry Rotation Model

After conducting a detailed analysis of the relationship between industry returns and industry prosperity, we have proposed the following strategy for constructing an industry rotation model. The first step in this model is to select the top five industries ranked by prosperity as the foundational investment portfolio. This selection strategy aims to leverage the cyclical economic patterns observed in these sectors, ensuring a robust and adaptive framework for optimizing returns.

To validate the effectiveness of the industry rotation model constructed based on industry prosperity, this study conducted a comprehensive test. We selected the period from February 28, 2013, to May 1, 2022, for an in-depth analysis of the model's performance in the market. This period covered a variety of market conditions, including bull markets, bear markets, and volatile periods, thus providing us with a good opportunity to evaluate the model's performance under different market environments. The main objective of the research is to observe whether this industry rotation model can consistently generate excess returns under actual market conditions and effectively avoid potential risks. Additionally, we compared it with the market benchmark index to assess its relative efficacy.

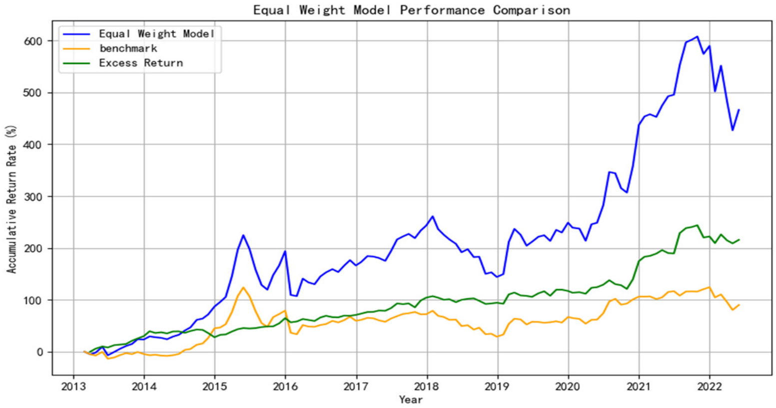

Fig.3 Equal weight model performance based on IP

Analysing the performance of this model in the financial markets over the past decade, we found that the model's annualized return rate is 22.40%, and its annualized excess return rate is 13.17%, significantly outperforming the market benchmark (see Fig. 3).

This disparity reveals the model's potential advantage in capturing industry rotations. Additionally, the model's maximum drawdown rate is -36.18%, while the maximum drawdown rate for excess returns is -10.43%. These two indicators together point to an investment strategy that maintains relative stability during market downturns. In terms of risk-adjusted returns, the equal-weight model's annualized Sharpe Ratio is 0.845, indicating that the model provides investors with higher risk-adjusted returns. Furthermore, the model's annualized Information Ratio of 1.106 further confirms its consistency and stability in excess returns relative to volatility, suggesting the model's ability to consistently outperform the market benchmark over multiple periods.

To enhance the performance of our model, we introduced an optimization strategy to enhance its practical application. The core of the optimization is to adjust the index weights Wi, maximizing the expected return of the portfolio (Wi*IP), where IP is the previously defined industry prosperity. The optimization process follows several key constraints:

1.Tracking Error Control: Keep the annualized tracking error within m to ensure the stability of the model's performance.

2.Industry Deviation Control: Limit industry deviation to within n to ensure the rationality of industry distribution.

3.Weight Limit: Set a maximum weight limit of x to maintain full-position operations.

The optimization operation of the model is performed at the end of each month. The base pool is selected from the top five industries ranked by prosperity.

The objective function and constraints of the optimized model are as follows:

$$\boldsymbol{max}(\,\boldsymbol{w_i} * \boldsymbol{IPTS}) \tag{13}$$

$$s.t.\, w_i \Sigma w < m \tag{14}$$

$$0 \leq w \leq x \tag{15}$$

$$max|w_0 - w_i| < n \tag{16}$$

$$\Sigma w = 1 \tag{17}$$

If the number of industries in the base pool is greater than or equal to 3, it indicates that high-prosperity industries are less congested, and we would increase our risk preference, setting the annualized tracking error m to 0.2, industry deviation base n to 0.3, and the weight limit x to 0.35. Conversely, if the number of industries in the base pool is less than 3, it suggests that high-prosperity industries are more congested, and we would decrease our risk preference, setting the annualized tracking error m to 0.1, industry deviation base n to 0.1, and the weight limit x to 0.25.

After applying this optimization strategy to our industry prosperity, we conducted tests in the actual market. The test results are shown in the following graph (see Fig. 4):

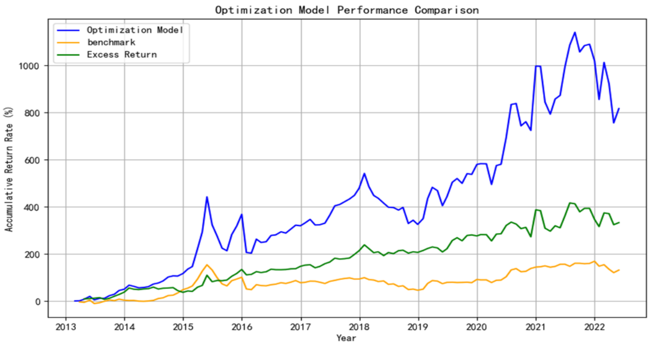

Fig.4 Optimising model performance based on IP

To better compare the changes in the model before and after optimization, this paper has compiled the relevant performance of both in the market (see Tab. 2):

Tab.2 Comparison of the effects of equal-weighted and optimisation models

	Equal weight model	Optimization model
Annual rate of return	22.39%	30.46%
Annualized excess return	13.17%	18.54%
Maximum retracement rate	36.18	40.08%
Excess maximum retracement	10.43%	19.45%
Shape ratio	0.8445	0.8508
Information rate	1.1063	0.9295

In our study, the annualized return rate of the equal-weight model is 22.39%, while the optimized model significantly increased to 30.46%, showcasing its obvious advantage in terms of returns (see Tab. 2). Moreover, the annualized excess return of the optimized model reached 18.54%, compared to 13.17% for the equal-weight model, further proving the effectiveness of the optimization strategy in capturing excess returns.

However, in terms of risk indicators, the maximum drawdown rate of the optimized model increased to -44.08%, compared to -36.18% for the equal-weight model, indicating that the optimized model undertook higher risks in the pursuit of higher returns. The maximum drawdown rate of the optimized model’s excess returns also increased to -19.45%, compared to -10.43% for the equal-weight model, further highlighting the importance of risk indicators. Nonetheless, the annualized Sharpe Ratio of the optimized model is 0.8508, slightly higher than the 0.8445 of the equal-weight model, suggesting that the optimized model still maintains a slight advantage in excess returns per unit of total risk.

From the perspective of the Information Ratio, the equal-weight model with a ratio of 1.1063 outperforms the optimized model's 0.9295, indicating that the equal-weight model may have an advantage in terms of consistency and stability of volatility relative to the benchmark. This difference may stem from the more concentrated weight distribution in specific industries in the optimized model, while the equal-weight model offers broader risk diversification.

Overall, the optimized model surpasses the equal-weight model in terms of return rate and annualized Sharpe Ratio, demonstrating its effectiveness under specific market conditions. However, the higher drawdown rate also implies a potential level of risk. Investors choosing a model need to balance returns and risks, while also considering their personal risk tolerance.

5 Conclusion

The primary contribution of this study lies in the development of a novel system for assessing industry prosperity, which serves as the foundation for an advanced industry rotation methodology. This model has demonstrated notable success in the stock market arena. Through a meticulous analysis of industry trends and market dynamics, we have developed indicators of industry prosperity. This methodology not only enhances investment returns but also plays a crucial role in managing investment risks. Our study addresses a notable gap in the literature concerning the application of industry rotation strategies within the Chinese market context. Furthermore, the industry prosperity model we have constructed significantly impacts the development of future financial products and the innovation of investment strategies, offering valuable insights to both investors and theoretical researchers. By integrating macroeconomic indicators with micro-market behaviours, our model exhibits significant potential in forecasting market trends and informing targeted investment decisions.

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