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Research and Strategy Optimization of Quantitative Trading Live Trading Based on Index Reconstruction

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Abstract: In recent years, index-enhanced investment strategies have grown increasingly sophisticated and complex, with the application of index reconstruction techniques becoming more widespread in quantitative trading. Nevertheless, the effectiveness of these strategies in real-world trading can be constrained by factors such as index fitting bias, model overfitting, and transaction costs. This article builds on the theoretical foundation of integrating index reconstruction with quantitative strategies and provides a comprehensive analysis of the challenges encountered in actual market operations. To address these issues, corresponding optimization methods are proposed, including the development of a dynamic index reconstruction mechanism, the use of regularization techniques to enhance model stability, and the refinement of execution path management to reduce costs. Empirical research is conducted to verify the effectiveness of these strategies, offering both theoretical insights and practical guidance for optimizing index-enhanced strategies in real-market environments.

Keywords: index reconstruction; quantitative trading; strategy optimization; real time backtesting

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1. Introduction

With the gradual adoption of quantitative investment concepts, index enhancement strategies, which occupy a middle ground between active management and passive replication, have attracted increasing attention from investors. In particular, amid the expansion of ETF index products, achieving excess returns while minimizing risk and tracking error has become a key focus of research and practical concern. Index reconstruction techniques optimize the selection of constituent stocks and weight allocation, thereby enhancing the original index and enabling more refined management in quantitative trading. However, in practice, index reconstruction strategies may encounter challenges such as overfitting errors, excessively complex models, and insufficient control over transaction costs, which can prevent the strategy from delivering the expected results in real trading. Therefore, a comprehensive analysis of these challenges in live-market operations is necessary, along with the exploration of optimization strategies tailored to practical scenarios. This article examines the relationship between index reconstruction and quantitative strategies from both theoretical and practical perspectives, and proposes a multidimensional optimization framework focused on tracking accuracy, model robustness, and execution efficiency, offering guidance for building effective and feasible index enhancement systems.

2. Theoretical Overview of Index Restructuring and Quantitative Trading

2.1. Basic Principles and Methods of Index Reconstruction

The index reconstruction strategy involves optimizing the selection of constituent stocks and the allocation of weights without fully replicating the benchmark index, while controlling risks and tracking errors, in order to achieve a superior risk-return profile and potentially generate excess returns above the benchmark. The primary objective of index reconstruction is to capture alpha relative to the benchmark while managing tracking error and risk exposure. Common reconstruction methods include multi-factor scoring, volatility adjustment, and industry-neutral optimization. By using quantitative methods to score and rank individual stocks, investors can select constituents with higher expected returns and allocate weights using approaches such as risk parity, minimum variance, or maximum information ratio. Additional constraints, including industry, style, and market capitalization, are applied to mitigate biases and reduce risk. Furthermore, rolling optimization mechanisms, such as monthly or quarterly position adjustments, are introduced to enhance the portfolio's responsiveness to market volatility. By combining elements of active management with passive investment, index reconstruction provides a stable and practical platform for quantitative strategies, and is widely applied in index-enhanced funds and smart beta products [1].

2.2. Quantitative Trading Model Framework and Strategy Types

Quantitative trading strategies systematically formulate, validate, and execute trading decisions through mathematical modeling and computer programming, essentially employing data-driven approaches to construct strategies while minimizing human biases. Generally, quantitative trading models can be divided into four layers: the data processing layer, the signal generation layer, the portfolio construction and optimization layer, and the execution and risk control layer. The data processing layer is responsible for collecting and cleaning market, fundamental, and macroeconomic data [2]. The signal generation layer leverages multi-factor models, statistical regressions, or machine learning methods to extract actionable market information. The portfolio construction layer allocates investment weights according to different objective functions-such as maximizing return or Sharpe ratio-while adhering to risk constraints. Finally, the execution layer employs methods such as high-frequency matching and VWAP/TWAP algorithms to manage transaction costs and slippage. Quantitative strategies include momentum reversal strategies, multi-factor stock selection, market-neutral strategies, event-driven strategies, and high-frequency arbitrage strategies. Each strategy is tailored to specific market conditions and cycles, providing diversified approaches for asset allocation and index enhancement (Figure 1).

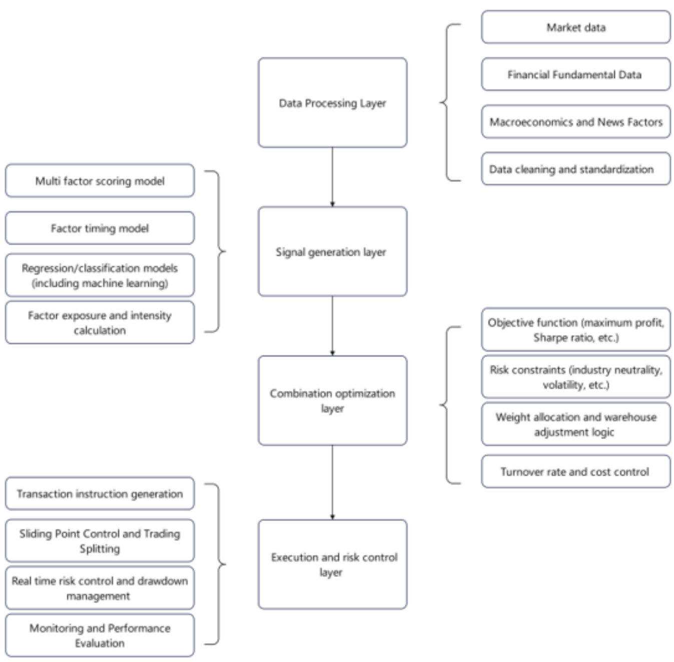

Figure 1. Quantitative Trading Model Framework Diagram.

2.3. Integration Logic of Index Reconstruction and Quantification Strategy

The integration of index reconstruction and quantitative trading strategies embodies a synergistic approach that combines passive replication with active enhancement. In traditional index investing, portfolio construction strictly follows the original index rules, limiting the potential for yield optimization. By employing quantitative strategies, investors can selectively screen constituent stocks and adjust their weights while maintaining risk management and benchmark adherence, thereby constructing enhanced portfolios that capitalize on factor exposures [3]. This integration can be understood from three perspectives. First, there is a shared objective: quantitative strategies aim to outperform the index, and index reconstruction provides the platform to implement these strategies. Second, there is complementarity in modeling: index reconstruction emphasizes structural control, while quantitative models focus on signal extraction and stock selection. Third, there is collaborative execution: algorithmic optimization converts signals into portfolio weights while accounting for constraints such as liquidity and transaction costs. The combination of these approaches not only increases portfolio management flexibility but also enhances the potential to achieve stable excess returns in live trading, making it a primary development direction for index-enhanced products.

3. Analysis of Problems in Real Trading

3.1. Index Fitting Deviation Leads to the Expansion of Strategy Tracking Error

In the process of index reconstruction, strategy design often requires balancing excess returns with risk constraints. However, differences in constituent stock selection, weight allocation models, or factor exposure controls can create structural deviations between the reconstructed portfolio and the original index, leading to increased tracking error. This issue is particularly pronounced when the target index undergoes frequent adjustments or when industry weights fluctuate significantly. Without a dynamic adaptation mechanism, a reconstructed portfolio may fail to capture index trends effectively, resulting in substantial tracking deviations. For example, when using the price-earnings (PE) ratio to rank stocks, companies with lower PE values receive higher scores, reflecting valuation advantages. In the A-share market over the past decade, the top 30% of portfolios with low PE ratios achieved an average annualized excess return of 3.5%, markedly outperforming portfolios with high PE ratios. In the short term, stocks with lower PE ratios tend to exhibit more stable upward trends.

Another important factor is momentum. Observing trends over the past month, stocks that have recently risen sharply are considered to exhibit short-term trend signals. Over the past five years, the monthly return of the top 20% momentum portfolio has exceeded the market by 1.2 percentage points. The momentum factor measures the degree of stock price change relative to the return over a prior trading period (such as 1 month or 3 months). The calculation formula is:

$$\text{Momentum}_t = \sum_{t=1}^{L} \ln\left(1 + r_n^{t-1}\right) \quad (1)$$

In the formula, r_n represents the stock return, and L denotes the preceding month. The momentum factor essentially reflects the inertia of stock prices and is particularly suited for short-term trading.

Additionally, dividend yield (DY) is commonly used to measure a stock's ability to generate dividends. Companies with higher dividend yields can provide investors with relatively stable cash flows and help mitigate the risk of stock price fluctuations. In practice, the dividend yield can be calculated using the following formula:

$$\text{DY} = \frac{\text{D}}{\text{P}} \quad (2)$$

In this formula, D represents the annual dividend per share, and P denotes the current stock price. Research indicates that companies with higher dividend yields generally exhibit lower annualized volatility, and their cumulative returns often outperform the market average.

By integrating these fundamental factors, investors can develop a multi-level scoring system, allowing for the selection of companies with reasonable valuations, strong performance, and stable dividends while adhering to established grading standards [4]. This approach helps reduce tracking errors arising from inappropriate index composition and enhances the durability and stability of the investment portfolio, as shown in Table 1.

Table 1. Comparison of Tracking Errors of Different Index Reconstruction Methods (Unit:%).

Reconstruction method	Component stock screening mechanism	Weight allocation method	Mean Tracking Error (TE)	maximum tracking error	Combination turnover rate
Original index replication method	Full replication	According to the original index weight	0.12	0.28	3.5%
Industry neutral multi factor reconstruction method	Factor scoring+industry constraints	Risk parity optimization	0.36	0.67	12.1%
Enhancement strategy for volatility constraint	Volatility filtering+liquidity screening	Maximizing information ratio	0.42	0.74	18.3%
Market capitalization weighted+factor adjustment method	Top Market Value+Alpha Ranking	Adjust market value weight	0.29	0.55	9.8%

Note: Tracking Error (TE)=√ Var (Rp − Rb), where Rp is the reconstructed portfolio return and Rb is the original index return. The turnover rate of combinations reflects the difficulty of execution and cost risk.

3.2. Overfitting of Strategy Parameters Leads to Unstable Performance in Real Trading

In constructing quantitative trading strategies, excessive reliance on historical data to adjust parameters can easily result in overfitting. Although overfitted models may demonstrate excellent backtesting performance within the sample, they often lack adaptability to future market conditions and can exhibit significant deviations in real-world performance. This issue is particularly prevalent in index enhancement strategies, including factor selection, scoring weight assignments, and timing threshold determinations. Fine-tuning parameters excessively may obscure the effectiveness of genuine signals. Moreover, optimizing solely within the sample ignores practical considerations such as market volatility, policy changes, and liquidity fluctuations, potentially leading to drawdowns or strategy failure in actual implementation. For instance, strategies that emphasize small-cap stocks or high-turnover factors are more susceptible to liquidity constraints during extreme market conditions. In summary, parameter overfitting undermines the stability and accuracy of strategies, potentially misleading investors and increasing trading risks, As shown in Table 2.

Table 2. Comparison of backtesting returns and stability within and outside the sample (unit:%).

Strategy model type	Annual return within the sample	Annualized returns outside the sample	Profit deviation	Maximum drawdown (in/out of sample)	Information ratio (in/out of sample)
Original Multi Factor Model	15.8	7.2	-8.6	6.5% / 12.3%	1.25 / 0.63

Model after parameter tuning (overfitting)	21.4	5.9	-15.5	5.2% / 14.7%	1.68 / 0.48
Regularized factor model	14.3	12.1	-2.2	7.8% / 8.2%	1.18 / 1.03
Rolling training model	13.9	11.6	-2.3	8.1% / 8.5%	1.14 / 0.97

Note: Income deviation = annualized return within the sample − annualized return out of sample. The Information Ratio measures the ability to generate excess returns per unit of risk, with higher values indicating better performance. Although the overfitted model performs exceptionally within the sample, out-of-sample returns decline significantly, indicating limited robustness of the strategy.

3.3. Low Execution Efficiency Leads to Continuous Increase in Transaction Costs

The critical link between quantitative strategy modeling and actual trading lies in execution. In real markets, however, poor integration between the model and the trading system-such as delayed order matching, excessive slippage, and trading shocks-can reduce execution efficiency and increase transaction costs. For instance, in stocks with high turnover or low liquidity, large orders may trigger market shocks, causing transaction prices to deviate from expected signals and diminishing strategic returns. Furthermore, the absence of dynamically adjusted execution algorithms makes it difficult to modify order-splitting methods based on real-time market depth and trading volume, further exacerbating slippage risks. In the context of index enhancement strategies, excessive position adjustments not only incur additional transaction fees but also destabilize the portfolio structure, ultimately affecting long-term strategy returns (see Table 3).

Table 3. Comparison of Cost Composition of Actual Trading for Different Strategy Types (Unit:%).

Policy type	Annual turnover rate	Average sliding point cost	Handling fee cost	impact cost	Total transaction cost	Cost to annualized revenue ratio
Traditional index replication strategy	20%	0.03	0.05	0.01	0.09	5.2%
High frequency multi factor rotation strategy	180%	0.12	0.21	0.08	0.41	22.5%
Optimize execution and enhance strategies	90%	0.06	0.12	0.03	0.21	11.1%
Passive holding+low-frequency adjustment strategy	35%	0.02	0.06	0.01	0.09	4.8%

Note: Slippage cost refers to the loss resulting from deviations between the actual transaction price and the theoretical signal price. Impact cost represents the market disturbance caused by large transactions. The cost-to-annualized-return ratio is calculated as total transaction costs ÷ strategy annualized return, reflecting the extent to which transaction costs erode returns.

4. Optimization Frameworks to Enhance Index With Limited Tracking Errors

In optimizing index reconstruction, the selection and combination of factor signals directly influence the strategy's final performance. These signals determine whether the strategy can generate excess returns and outperform the original index. To achieve index enhancement, this study primarily employs the price-earnings ratio (PE), price momentum (Momentum), and dividend yield (DY) as the core factors [5].

The PE factor effectively identifies undervalued stocks, which often exhibit greater potential for rebound. The momentum factor captures short-term price trends, highlighting stocks that have recently performed well and are likely to continue their upward trajectory. The dividend yield factor targets companies with stable and relatively high dividend payouts, providing more consistent income during periods of market volatility.

By flexibly adjusting the weights of each factor, the investment portfolio can be optimized to outperform the benchmark while maintaining tracking error within a reasonable range. This multi-factor optimization approach not only enhances risk-adjusted returns but also establishes a robust framework for implementing index-enhanced strategies.

4.1. Optimizing Refactoring Logic to Improve Index Tracking Accuracy

To mitigate tracking error expansion caused by index fitting bias, it is necessary to incorporate optimization modeling techniques during the reconstruction process to better align the portfolio with the return and risk characteristics of the target index. Two specific approaches are commonly employed. First, a multi-factor scoring method combined with industry-neutral constraints is used in the selection of constituent stocks, ensuring that the portfolio aligns with the benchmark in terms of factor exposures and industry composition. Second, an optimization model based on minimizing tracking error is applied in weight allocation. Its mathematical formulation is expressed as follows:

$$\min_{w} TE = \sqrt{(R_p - R_b)^T \cdot \sum \cdot (R_p - R_b)} \tag{3}$$

Among them, w is the combination weight vector, $R_p = w^T \cdot R$ represents the combination return, R_b is the benchmark index return, and ∑ is the covariance matrix of asset returns. The goal is to make the portfolio return as close to the benchmark as possible under multidimensional constraints such as industry, turnover rate, and upper and lower limits of individual equity. In addition, to avoid static structural failure, a rolling optimization mechanism can be introduced to dynamically update and reconstruct the portfolio based on market changes on a monthly or quarterly basis, improving the dynamic adaptability and robustness of index tracking and ensuring the stable performance of the strategy in real trading.

4.2. Suppressing Model Overfitting to Enhance Real-Time Robustness

To ensure the stable performance of quantitative strategies in real markets, a series of mechanisms should be implemented to mitigate model parameter overfitting. First, techniques such as out-of-sample validation and rolling-window testing are employed to assess the strategy's robustness, preventing the model from being effective only over a limited historical period. Second, during factor selection and parameter determination, degrees of freedom are controlled, and key factors with economic significance and long-term effectiveness are retained, reducing redundancy and filtering out noise in factor combinations. Additionally, modeling techniques such as regularization constraints, hierarchical training, and heterogeneous sample testing are applied to further prevent overfitting and enhance the strategy's generalizability and adaptability. During backtesting, scenarios encompassing multiple markets, cycles, and styles are constructed to evaluate performance consistency under diverse conditions. Third, a real-time monitoring mechanism for portfolio holdings is established to promptly detect deviations between the strategy and market behavior and adjust dynamic parameters accordingly. Collectively, these measures reduce the impact of overfitting on actual performance and improve the practicality and long-term stability of quantitative models [6].

4.3. Fine Tuned Execution Control to Reduce Transaction Costs

Transaction costs are a critical factor affecting the actual returns of quantitative strategies, particularly in high-turnover approaches. Establishing a refined execution control system can mitigate the negative impact of transaction frictions. From a trading perspective, methods such as block trading, time-weighted average price (TWAP), and volume-weighted average price (VWAP) can be employed to optimize execution. These methods dynamically adjust order placement based on real-time market liquidity, reducing market impact and slippage. TWAP and VWAP, in particular, distribute trades evenly over a set period, avoiding large orders during market fluctuations, smoothing execution, and minimizing unnecessary market disruptions.

Order preprocessing technology is essential for splitting and classifying large orders. By leveraging real-time order information, the system can select the optimal execution method and time window. For example, during periods of low liquidity, orders can be delayed or divided into smaller batches to reduce market pressure. Utilizing trading simulation within multi-strategy backtesting systems allows potential execution challenges to be anticipated and strategies optimized accordingly.

During strategy design, transaction costs should be incorporated into the optimization objective. Estimating expected transaction costs during strategy development balances costs and benefits, preventing the pursuit of factor signal returns from being undermined by actual trading expenses. This approach is particularly relevant for high-frequency strategies, which typically involve elevated turnover and substantial transaction costs that can erode excess returns.

Empirical results demonstrate that optimized execution significantly reduces transaction costs. For example, the traditional index replication strategy has an annual turnover rate of approximately 20%, total transaction costs of 0.09%, and a cost-to-return erosion rate of 5.2%. In contrast, a high-frequency multi-factor rotation strategy with a turnover rate of 180% incurs total costs of 0.41%, consuming 22.5% of total returns and nearly offsetting excess gains. Through optimized execution, the turnover rate of the enhanced strategy drops to 90%, total costs decrease by 0.21%, and the cost proportion falls to 11.1%, effectively mitigating the dilution of returns. Meanwhile, a low-frequency inventory adjustment strategy maintains a turnover rate around 35%, with total costs of 0.09% and a cost share of 4.8%, demonstrating relatively stable performance.

Simulation tests further indicate that switching high-frequency strategies from regular market orders to TWAP/VWAP execution can reduce average slippage by 30%-40% and impact costs by approximately 0.05%-0.07%. This optimization can ultimately increase annualized profits by 2%-3%, illustrating that refined execution control not only lowers transaction costs but also enhances long-term market performance. The common factors and their calculation formulas are summarized in Table 4.

Table 4. Common Factors and Their Calculation Formulas.

Factor	Calculation formula	Explanation
Price-earnings ratio (PE)	$\mathrm{PE} = \frac{\mathrm{P}}{\mathrm{E}}$	P represents the current price of the stock and E represents earnings per share. A low PE ratio usually indicates a lower valuation and higher potential returns.
Momentum factor	$\mathrm{Momentum_t} = \sum_{t=1}^{L} \ln(1 + r_n^{t-1})$	Measuring the short-term changes in stock prices reflects the trend and inertia of stocks.
Dividend yield (DY)	$\mathrm{DY} = \frac{\mathrm{D}}{\mathrm{P}}$	D represents the dividend per share and P represents the current price. A high dividend yield usually indicates that a company's cash flow is relatively stable.

Volatility	$\text{Volatility}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i-\overline{P})^2}$	The degree of fluctuation in stock prices is measured. A higher volatility usually indicates greater risk.
Volume-weighted average price (VWAP)	$\text{VWAP}=\frac{\sum_{i=1}^{n}(P_i \times Q_i)}{\sum_{i=1}^{n}Q_i}$	VWAP reflects the weighted average of transaction prices and volumes within a specific time period and is suitable for optimizing execution.
Time-weighted Average Price (TWAP)	$\text{TWAP}=\frac{1}{T}\sum_{i=1}^{T}P_i$	TWAP controls market influence by evenly distributing trading volume, and is particularly suitable for block trades.

5. Research is limited to prospects

This study focuses on the modeling and construction of medium-frequency multi-factor strategies, as well as their practical analysis, without addressing high-frequency strategies or cross-market index adaptation. Additionally, because some backtesting data are based on historical static samples, the dynamic effects of liquidity and market volatility in real trading may not be fully captured, potentially resulting in discrepancies between simulation and actual performance.

Future research could explore more advanced algorithmic trading frameworks, such as machine learning-based factor mining and adaptive index construction, to enhance the strategy's adaptability and optimization capabilities. Furthermore, integrating cross-market asset data and high-frequency trading information could facilitate the development of a multidimensional index enhancement system encompassing A-shares, Hong Kong stocks, and ETF products, thereby expanding both the depth and breadth of the analysis.

6. Conclusion

This article examines the application of index reconstruction in quantitative trading, identifies key challenges in real-market implementation-such as widening tracking errors, parameter overfitting, and elevated trading costs-and proposes corresponding optimization strategies. Specifically, a dynamic index reconstruction mechanism is introduced to mitigate the risks associated with overfitting, while refined execution path control reduces transaction costs, providing a practical approach to enhancing both the robustness and return performance of strategies in real-time trading environments.

The study highlights the critical importance of aligning theoretical models with actual market conditions, as this alignment largely determines the effectiveness and reliability of quantitative strategies. Empirical analysis demonstrates that multi-factor selection, dynamic weighting, and disciplined execution control can collectively improve risk-adjusted returns and maintain portfolio stability under varying market conditions.

Looking forward, emerging technologies such as high-frequency data analysis, reinforcement learning, and adaptive machine learning models offer the potential to develop more flexible and intelligent index enhancement strategies. By integrating cross-market data and real-time liquidity information, future research can construct multidimensional frameworks that further optimize performance across different asset classes, trading frequencies, and market environments. Overall, this work provides both a theoretical foundation and practical reference for advancing intelligent quantitative trading and the continuous evolution of index-enhanced investment strategies.

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