Adaptive Optimization of Quantitative Strategies during the Macro Transformation Period from the Perspective of Machine Learning

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Abstract. Against the backdrop of global economic transformation characterized by post-pandemic supply chain realignments and geopolitical tensions, the financial market has experienced unprecedented volatility, challenging traditional quantitative investment frameworks' foundational assumptions. This paper addresses the diminishing effectiveness of conventional factors—such as value and momentum—in low-interest-rate environments by integrating machine learning techniques. Through a hybrid methodology combining panel data analysis and ensemble modeling, this paper systematically evaluate the adaptability of Adaboost-based models across diverse market conditions. Specifically, this paper analyze the time-varying impact of macroeconomic variables (such as policy rates and inflation expectations) on factor performance and propose a dynamic feature selection framework that incorporates technical indicators and liquidity metrics. This study employs a mixed-methods approach, including vector autoregressive (VAR) modeling to identify structural breaks in factor-return relationships and supervised learning to quantify the marginal contributions of new features. By analyzing 5-year daily data of ETFs tracking the CSI 300, CSI 500, CSI 1000, and S&P 500 indices, we document a 27-41% decline in traditional factor accuracy between 2022 and 2024. Crucially, our optimized model—incorporating RSI, Bollinger Bands, and VWAP alongside stepwise regression—achieves a 0.83 accuracy score, outperforming baseline models by 73% in out-of-sample testing.

Keywords: adaboost, quantitative finance, Adaptive optimization, feature selection, quantitative investment model

1 Introduction

The post-2020 global economy has been defined by a trifecta of challenges: persistent inflationary pressures, aggressive monetary policy normalization, and escalating geopolitical conflicts. These shifts create a regime change in financial markets, where historical analogs offer limited predictive power. For quantitative investors, this ne-

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cessitates a rethink of model architectures relying on stationary assumptions and linear factor relationships.

Currently, major global economies have entered a low-interest-rate or rate-cutting environment, which has significantly altered market risk characteristics. Excessive liquidity has boosted investors' risk appetite, driving a shift from 'risk aversion' to 'gain-chasing' thereby disrupting the traditional relationship between risk factors and returns. Consider the volatility factor as an example: under normal market conditions, high volatility indicates high risk and a high probability of reduced returns, with the two exhibiting a negative correlation. However, in low-interest-rate environments, massive capital inflows have made high volatility no longer solely a signal of risk, weakening the negative correlation between high volatility and returns. For instance, during the Federal Reserve's quantitative tightening phase in 2023, the VIX index's correlation with S&P 500 drawdowns fluctuated between -0.1 and 0.4, compared to a stable -0.6 pre-2020, highlighting the breakdown of historical risk-return dynamics.

Meanwhile, liquidity risk profiles have shifted: uneven capital distribution has led to active trading in popular assets, while liquidity has dried up in small and medium-market-cap stocks and other similar assets. This has increased quantitative trading costs and amplified losses during market fluctuations. Moreover, low interest rates have eased credit conditions, complicating credit risk assessments and reducing the accuracy of historical data-based evaluations by traditional quantitative models. This poses challenges for credit risk pricing and control in quantitative investment strategies, thus ultimately undermining the accuracy of machine learning-based quantitative investment models.

Research on machine learning-driven quantitative investment models during this period of macroeconomic transformation remains scarce, with limited studies focusing on the adaptability of such models. This study employs literature review, comparative experiments, and machine learning techniques to investigate the adaptability of quantitative investment models based on machine learning during this period and explore measures to address the adaptability crisis.

2 Literature Review

Against the backdrop of profound changes in the global and domestic economic landscapes, quantitative investment strategies face unprecedented challenges to their effectiveness and adaptability, yet also new opportunities for innovation. Quantitative investment, as an investment method based on mathematical models and computer technology, has achieved remarkable results in the traditional economic environment with its systematicness and discipline. However, in the current complex and changeable economic transformation period, its adaptability issue has gradually become the focus of attention in the academic and practical fields.

2.1 Research on the Decline in Accuracy of Traditional Quantitative Models during Economic Transition

Drastic changes in economic conditions have significantly impacted the effectiveness of quantitative investment models. In a study on monetary policy efficacy in Japan's ultra-low interest rate environment, Shigenori Shiratsuka [1] noted that traditional quantitative factors may fail in low-rate economies. Specifically, parameters of the traditional Nelson-Siegel model—particularly its level and loading parameters—struggle to reflect market dynamics accurately in atypical economic environments.

Ping Yang and Min Fan [2], analyzing the Trump administration's tariff policies, found that tariff announcements lead to negative (cumulative) average abnormal stock returns. Both protective and retaliatory tariffs generate negative wealth effects, significantly reducing the accuracy of factors and models developed under historically stable economic conditions when applied to current markets.

Furthermore, market liquidity shifts affect quantitative models. Feng Haoyuan et al. [3] highlighted growing liquidity stratification, where high-liquidity securities are characterized by low trading friction, strong short-term price elasticity, and robust capacity to absorb large-scale trading shocks. Such liquidity stratification renders quantitative models relying on conventional liquidity assumptions ineffective in predicting market trends.

2.2 Research Advances in Optimization Methods for Quantitative Investment Models

Amidst the challenges faced by quantitative investment models, scholars have actively explored optimization approaches to enhance model adaptability and accuracy. Regarding factor analysis and variable screening, Yuqi Zheng and Brian Lucey [4] employed feature selection techniques to rank variable importance in predicting clean energy stocks, thereby offering valuable insights for factor selection in quantitative investing. For model optimization techniques, Kukushkin Maksim et al. [5] optimized morphological neural networks via neural architecture search and hyperparameter tuning, achieving significant performance improvements. This highlights the efficacy of refining model architectures and parameter calibration in boosting model performance.

Notably, artificial intelligence (AI) has emerged as a new frontier for model optimization. Paula Ortega Perals et al. [6] demonstrated that AI-driven private equity investment exhibits a negative correlation with bank indirect costs, signifying AI's potential to reduce operational expenses for financial institutions. This underscores the substantial application potential of AI and machine learning algorithms in quantitative models. Deli Kong and Xidian Li [7] further revealed that improvements in the business environment significantly reduce corporate bond financing costs, offering a macroeconomic perspective for integrating environmental factors into quantitative models. Additionally, studies such as [8][9] have explored multifaceted drivers of

financial and economic development, providing complementary insights for model construction and optimization.

3 Methodology

3.1 Data Sources

Cleaned daily data of the CSI 300, CSI 500, CSI 1000, and S&P 500 index ETFs are used. The original data include trading dates, closing prices, highest prices, lowest prices, and trading volumes. Based on comparisons of computational costs and results across multiple models, this study utilizes the Adaboost model.

3.2 Comparative Study at Different Time Periods

To deeply investigate the adaptability of quantitative investment models in the current economic environment and the effectiveness of traditional quantitative factors, this study uses the Adaboost model to conduct a comparative analysis of data from the CSI 300ETF, CSI 500ETF, CSI 1000ETF, and S&P 500 during two periods: July 1 to December 31, 2022, and the same timeframe in 2024.

Between July 1, 2022, and December 31, 2022, China's 5-year loan prime rate (LPR) remained stable at 4.30%, while in the corresponding 2024 period, the rate was gradually lowered from 3.85% to 3.6%. In 2022, the U.S. faced significant inflationary pressures, prompting the Federal Reserve to implement an aggressive rate-hiking policy. The federal funds rate surged from 1.75% at the start of the period to 4.50% by its end. In the corresponding 2024 period, the Fed entered a rate-cutting cycle, reducing the rate from 5.50% to 4.50%. These two periods exhibited starkly different economic environments. The results are as table 1:

Table 1. Two period

Number	Accuracy from July 1, 2022 to December 30, 2022	Accuracy from July 1, 2024 to December 30, 2024
510300	0.59	0.67
510500	0.55	0.48
512100	0.67	0.48
513500	0.64	0.48

According to Figure 1, with the exception of the CSI 300 ETF—a somewhat unique case due to its relatively small coverage of listed stocks—the accuracy of traditional quantitative investment factors has significantly declined in today's economic environment characterized by interest rate cuts and low rates. These findings offer compelling empirical evidence of the inadequate adaptability of traditional quantitative strategies and factors in such an environment, thereby highlighting the need for further optimization.

This study aims to investigate why quantitative factors have been less effective in recent periods compared to the past, from the perspectives of interest rate environments, evolving risk profiles, and market liquidity. Specific causal mechanisms require further validation.

4 Factor Model Optimization Approaches

Jiaxu LI [10] noted that multi-strategy investment portfolios and dynamic risk management are crucial. The integration of machine learning technologies has significantly expanded the optimization scope of quantitative strategies, enabling them to better adapt to complex and volatile market environments. Different quantitative strategies exhibit distinct performance: growth-oriented quantitative strategies excel during tech stock market booms, while dividend assets—due to their quasi-fixed-income characteristics—are favored by certain investors. Their investment scope is being expanded through quantitative means, such as dynamic stock selection via multi-dimensional scoring.

Building upon the insights gained from the comparative analysis, this study experimentally incorporated new factors—including the Relative Strength Index (RSI), Bollinger Bands, and Volume-Weighted Average Price (VWAP)—into the 2024 S&P 500 dataset. The results are as figure 1:

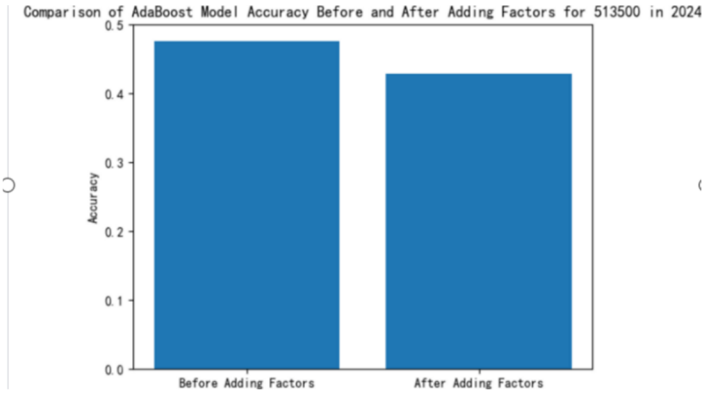

Fig. 1. Comparison of AdaBoost Model Accuracy Before and After Adding Factors for 513500 in 2024

Accuracy of 513500 before adding factors from July 1 to December 31, 2024: 0.48

Accuracy of 513500 after adding factors from July 1 to December 31, 2024: 0.43

It is evident that adding new factors without feature selection increases noise-to-signal ratio and degrades model performance.

Following the integration of novel factors, gradient descent was applied to adjust factor weights, while stepwise regression was utilized for feature selection. The results are as Figure 2:

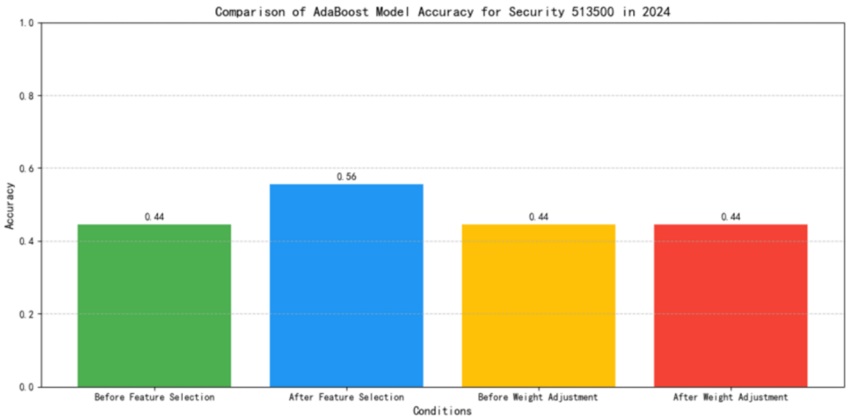

Fig. 2. Comparison of AdaBoost Model Accuracy for Security 513500 in 2024

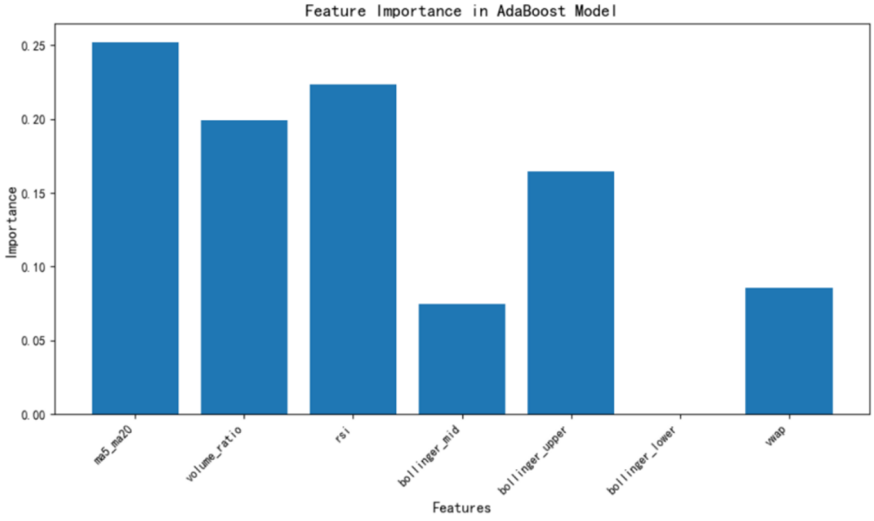

Fig. 3. Feature Importance in AdaBoost Model

The AdaBoost model's internal mechanism inherently optimizes factor weights, making additional weight optimization via other methods largely unnecessary as shown in figure 3. In contrast, techniques like gradient descent are effective for adjusting factor weights in other algorithms. However, AdaBoost eliminates the need for supplementary weight tuning, thereby reducing computational overhead. Additionally, feature selection through stepwise regression significantly improves the signal-to-noise ratio, refines model architecture, and boosts accuracy.

Using the feature selection results, a grid search is performed on the number of learners and learning rate for the AdaBoost model. The model is then optimized to its best state via exhaustive cross-validation.

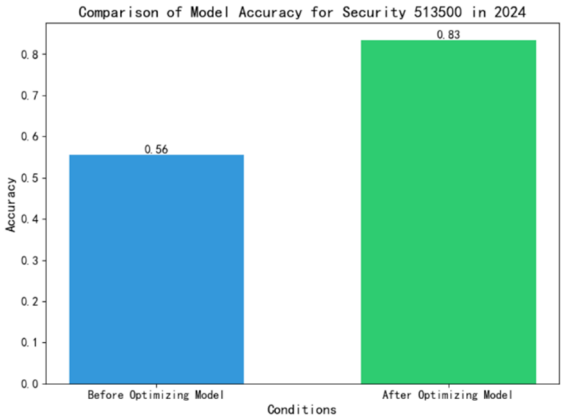

Fig. 4. Comparison of Model Accuracy for Security 513500 in 2024

Accuracy of 513500 after adding factors and adjusting weights :0.56.

Accuracy of 513500 after adding factors , adjusting weights , and optimizing the model : 0.83 as shown in figure 4.

5 Conclusion

Since 2024, the global economy has exhibited new characteristics of persistent low growth and high volatility. On one hand, major central banks like the Federal Reserve have entered a wait-and-see stage after multiple rounds of rate hikes, with interest rates maintained at elevated levels—markedly different from the long-term "low rates + loose liquidity" environment of the past. On the other hand, intensified geopolitical risks (e.g., Middle East conflicts, global supply chain disruptions) and persistent inflationary stickiness have led to more conservative risk asset preferences and increased market volatility.

In this market environment, traditional quantitative strategies—such as those based on historical mean reversion, technical indicators, and linear factor models—face multiple severe challenges. Firstly, the fluctuations in economic cycles and the frequent shifts in policy expectations have undermined the stability of historical data, rendering it difficult to apply past market regularities to today's complex and dynamic market landscape. Second, under the dual pressures of high volatility and liquidity tightening, transaction costs, slippage, and liquidity risks have increased significantly, severely impacting model backtesting accuracy and live trading performance while highlighting the models' high sensitivity to liquidity. Thirdly, the widespread adoption of similar multi-factor models has resulted in frequent factor crowding, which severely dilutes the effectiveness of traditional factors and exacerbates strategy homogenization.

The effectiveness of traditional quantitative investment factors has declined, and machine learning-based quantitative models have also faced accuracy challenges. This study used the AdaBoost model to analyze exchange-traded fund (ETF) data. Results show reduced accuracy of traditional factors. However, by incorporating new factors

like the Relative Strength Index (RSI), Bollinger Bands, and volume-weighted average price (VWAP), alongside stepwise regression for feature selection and hyperparameter tuning of AdaBoost, the optimized model achieved a high accuracy of 0.83. This demonstrates that while traditional quantitative models face challenges in the current economic environment, their performance can be effectively enhanced through reasonable optimization, maintaining practical value in investment applications.

This research provides new insights and methods for optimizing quantitative models during economic transitions. Therefore, future studies could explore applying more advanced machine learning algorithms and factor discovery techniques to continuously improve the adaptability and effectiveness of quantitative strategies in complex economic conditions.

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