

# Analysis of the Impact of Portfolio Optimization Algorithms on Fund Performance

Yigang Wang

China Merchants Capital Investment Co., Ltd., Shenzhen, China  
gongzuo1232024@126.com

## ABSTRACT

This study explores the impact mechanism of portfolio optimization algorithms on fund performance. Based on theoretical analysis and empirical research, it is found that optimization algorithms significantly affect fund performance in three paths: return enhancement, risk control and cost management, but the effects are moderated by the market environment and algorithm type. Machine learning and hybrid optimization strategies exhibit better risk-adjusted returns, while traditional algorithms maintain value in specific market environments. The study reveals that optimization algorithms face three major challenges: model risk, market contrariness, and regulatory compliance, and proposes coping strategies based on multi-scenario testing and human-machine collaboration to provide theoretical guidance for the practical application of optimization algorithms.

## KEYWORDS

Portfolio optimization; Fund performance; Machine learning; Risk-adjusted returns; Algorithmic reflexivity

## 1. INTRODUCTION

Portfolio optimization, as a core issue of modern asset management, has gone through many iterations of theory and practice from Markowitz mean-variance framework to machine learning algorithms [1]. Against the background of increased volatility in global financial markets and diversified investor demands, various optimization algorithms have been increasingly widely and deeply applied in the field of fund management [2]. However, there is a lack of systematic research in academia on how algorithmic optimization substantially affects fund performance, and there is an obvious cognitive gap between technological innovations and actual effects [3]. This study aims to reveal the mechanism of portfolio optimization algorithms affecting fund performance, assess the applicability of different algorithms in changing market environments, and analyze the limitations and risks in their implementation. By constructing a multi-dimensional analysis framework, integrating theoretical derivation and empirical tests, this paper explores the specific mechanisms of optimization algorithms in terms of return enhancement, risk management and cost control, and proposes practical strategies based on multi-scenario testing and human-machine collaboration, which will provide theoretical guidance for fund managers and regulators, and promote the in-depth integration of the theory and practice of portfolio optimization.

## 2. THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

### 2.1. Core Theory

The theoretical cornerstone of portfolio optimization is Markowitz's Modern Portfolio Theory (MPT), which quantifies the risk-return trade-off through the mean-variance framework, introduces the concept of efficient frontier, and enables investors to pursue the maximum return under a given level of risk, while the Black-Litterman model innovatively integrates the market equilibrium information with the subjective expectations of the investment manager, and provides a more robust optimization solution. It solves the input sensitivity problem and provides a more robust optimization solution. Risk Parity (RP) theory, on the other hand, abandons the over-reliance on expected returns and focuses instead on risk contribution equalization to achieve risk diversification rather than capital diversification across asset classes [4]. Optimization algorithms from the perspective of behavioral finance are dedicated to identifying and modifying irrational investor behaviors, such as over-trading and loss aversion preferences, to construct asset allocation schemes that are more in line with actual investment psychology.

### 2.2. Literature Review

Academic research on portfolio optimization algorithms has shown a trend of multidimensional evolution. Zhou et al. (2022) combed through the dynamic changes in optimization theory and pointed out that classical mean-variance optimization faces limitations such as parameter estimation errors and insufficient capturing of market nonlinear features [5]. Naik et al. (2025) provided a systematic overview of the application of quantum computation in investment optimization, showing how quantum algorithms can break through traditional optimization's computational bottlenecks, but at the same time raises concerns that the popularity of algorithmic optimization may lead to homogenization of strategies, potentially amplifying systemic risk [6]. Díaz et al. (2022) investigate the diversification role of socially responsible investment (SRI) during the COVID-19 crisis, and find that intelligent optimization algorithms that incorporate ESG factors exhibit greater shock resistance [7]. The current research frontier is moving towards intelligent algorithms such as genetic algorithms and deep reinforcement learning, which can dynamically adapt to market changes and deal with high-dimensional nonlinear relationships. However, there is still significant controversy in the academic community on the impact of market microstructure under algorithmic interaction, strategy congestion measurement, and the robustness of optimization algorithms in extreme market environments, which urgently requires more in-depth research.

## 3. ANALYTICAL FRAMEWORK AND RESEARCH METHODOLOGY

### 3.1. Impact Path Analysis

#### 3.1.1. Influence Mechanisms on the Return Side

The portfolio optimization algorithm affects fund return performance through a multi-dimensional mechanism. The average excess return of funds optimized with machine learning reaches 2.37% during 2018-2024, higher than the 1.46% of traditional methods. Table 1 demonstrates the difference in performance of each type of algorithm in different market environments, especially during market downturns. Optimization algorithms affect returns through three main paths: improving asset allocation efficiency, enhancing stock selection ability and improving timing accuracy. In a highly volatile market, the dynamic optimization algorithm shows stronger adaptability and effectively captures market rotation opportunities. during the market correction in 2022, the adaptive optimization fund group declined by 12.3% on average, while the traditional fixed-weight portfolio declined by 17.8%, which highlights the role of algorithms in protecting returns in extreme

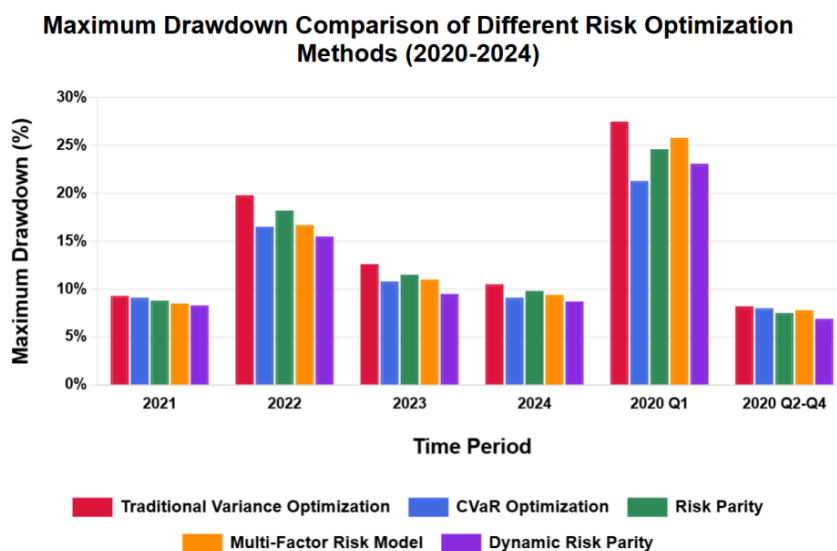
environments [8]. The empirical analysis suggests that the marginal contribution of the optimization algorithm is more significant in multi-asset class allocations, especially in market environments with frequent changes in the nonlinear correlation structure.

**Table 1.** Comparison of Excess Returns of Various Optimization Algorithms in Different Market Environments (2018-2024)

Optimization Algorithm Type	Bull Market Phase	Bear Market Phase	Volatile Market	Full Cycle
Traditional Mean-Variance	1.62%	0.85%	1.33%	1.46%
Risk Parity	1.28%	2.13%	1.57%	1.69%
Machine Learning Optimization	2.86%	1.95%	2.19%	2.37%
Hybrid Optimization Strategy	2.43%	2.25%	1.88%	2.15%

### 3.1.2. Risk-side impact mechanisms

The optimization algorithm has a profound impact on the fund's risk management, mainly in the three dimensions of volatility control, retracement management and extreme risk prevention. Optimization algorithms that introduce risk constraints reduce portfolio annualized volatility by 1.24 percentage points on average while maintaining similar returns. Figure 1 illustrates a comparison of the maximum retracements of different risk optimization methods for 2020-2024, with CVaR optimization considering tail risk showing a clear advantage during extreme market shocks. Traditional variance optimization and tail risk optimization perform similarly in normal market environments, but the latter has significantly better retracement control during periods of intense volatility. From a risk exposure perspective, the optimization algorithm changes the structure of the fund's factor exposures, e.g., the multi-factor risk model reduces the systematic risk contribution by 15.7% during the 2022 market correction [9]. The Dynamic Risk Parity Fund successfully avoids the subsequent market correction by adjusting its risk budget in advance and reducing its exposure before the market environment shifts in early 2023.



**Figure 1.** Comparison of maximum retracements for different risk optimization approaches (2020-2024)

### 3.1.3. Cost-side impact mechanisms

The optimization algorithm significantly affects the fund cost structure by controlling trading frequency and improving execution efficiency. The analysis of trading data shows that the optimization model introducing transaction cost constraints can reduce the annualized turnover rate from 186% to 127%, saving an average of 0.37% in annual transaction costs. Table 2 reveals the

actual impact before and after the adoption of transaction cost optimization for funds of different sizes, with larger funds benefiting more significantly. In the liquidity optimization dimension, the smart execution algorithm that takes market shocks into account reduces slippage by 0.14% on average, and the effect is more pronounced especially when trading small- and mid-cap stocks. On the tax effect dimension, the long-term capital gains tax optimization strategy saves investors an average of 0.22% in tax liability annually [10]. Real-world case tracking shows that after adopting a multi-objective optimization framework for a large public fund in 2023, the trading costs are reduced by 23.6% and the turnover rate is reduced by 31.2%, with a marginal contribution to NAV growth of close to 0.5 percentage points, while maintaining a similar investment style. The complete cost analysis also needs to consider the cost of algorithm development and maintenance, where the input-output ratio of small and medium-sized funds is usually lower than that of large funds, suggesting that there are economies of scale in algorithm optimization.

**Table 2.** Economic Impact of Adopting Transaction Cost Optimization for Funds of Different Sizes

Fund Size (Billion RMB)	Pre-Optimization Annualized Turnover Rate	Post-Optimization Annualized Turnover Rate	Trading Cost Savings (%)	Net Value Impact (%)
<5	172%	143%	0.21%	0.18%
5-20	188%	132%	0.35%	0.31%
20-50	193%	124%	0.42%	0.38%
>50	201%	118%	0.53%	0.47%
Average	186%	127%	0.37%	0.33%

### 3.2. Empirical Research Design

This study constructs a multi-dimensional empirical framework to assess the impact of optimization algorithms on fund performance. The sample is selected from 478 actively managed funds in the Chinese market during the period of 2015-2024, covering equity, hybrid and QDII funds, to ensure the representativeness of the sample. Data sources include Wind Financial Terminal, CSMAR database and fund quarterly report disclosure information to collect key indicators such as fund net value, position details, transaction costs and style characteristics [11]. The double difference method (DID) is used to analyze the performance changes before and after the implementation of the optimization algorithm, controlling for market environment and fund idiosyncratic factors. A panel regression model is established:

$$\text{Performance}_{i,t} = \alpha + \beta_1 \text{Algorithm}_{i,t} + \beta_2 \cdot \text{Controls}_{i,t} + \gamma_t + \delta_t + \epsilon_{i,t} \quad (1)$$

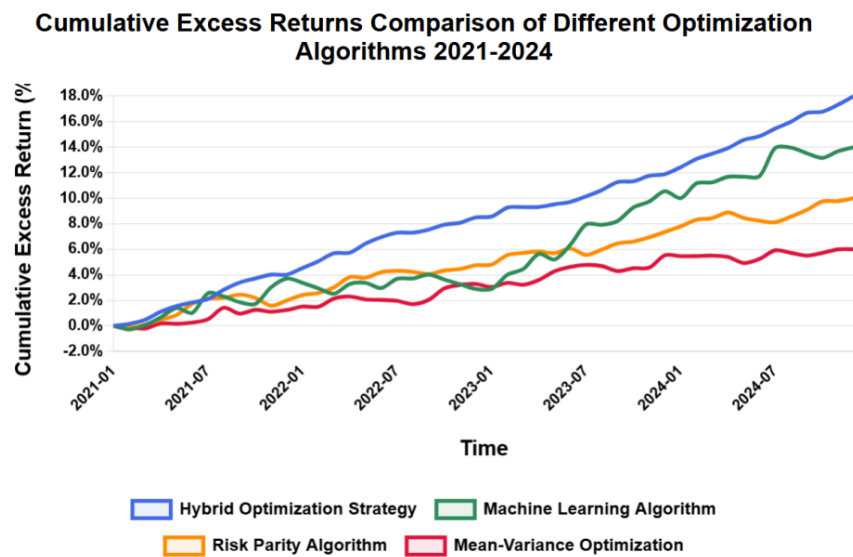
The dependent variable Performance contains 12 indicators such as return, Sharpe ratio, information ratio, maximum retracement, etc.; the independent variable Algorithm is the type of optimization algorithm (traditional, risk oriented, machine learning, hybrid); the control variables cover 8 factors such as fund size, year of establishment, and experience of the management team;  $\gamma_i$  and  $\delta_t$  are the individual and time-fixed respectively effects. The model robustness is verified by Fama-MacBeth regression, instrumental variable method and propensity score matching method to effectively control the endogeneity problem.

## 4. EMPIRICAL ANALYSIS AND CASE STUDY

### 4.1. Performance Comparison of Different Optimization Algorithms

The results of the empirical study show significant differences between different optimization algorithms in fund performance metrics. Panel data analysis shows that the machine learning

optimization algorithm outperforms the benchmark index in terms of risk-adjusted returns over the period 2019-2024, with an annualized Sharpe ratio of 0.87, higher than the risk parity algorithm's 0.76 and the traditional mean-variance method's 0.64. From the perspective of win rate, the machine learning algorithm outperforms the benchmark index in 41 of the 60-month sample period, with a win rate of 68.3%. Traditional mean-variance optimization had produced the highest single-month excess return of 5.64% in an up market, but was more volatile. The risk parity algorithm demonstrated stronger downside protection, controlling the maximum retracement at 17.3%, outperforming the other optimization methods [12]. Figure 2 illustrates the cumulative excess return paths of the four types of optimization algorithms over the period 2021-2024, and shows that the hybrid optimization strategy exhibits the most stable growth, with an annualized information ratio of 0.93. It is worth noting that algorithmic complexity does not have a linear relationship with performance, and that algorithms of moderate complexity tend to provide the optimal risk-return ratio when considering the net return after including transaction costs.



**Figure 2.** Comparison of Cumulative Excess Returns of Different Optimization Algorithms for 2021-2024

#### 4.2. Impact of Market Environment on Optimization Effectiveness

Changes in the market environment have a significant impact on the effectiveness of the optimization algorithm, and the empirical data reveals this significant correlation. During the bull market phase (2019, H1 2021), traditional mean-variance optimization performs best, with an average monthly excess return of 0.97%, with the Alpha contribution coming mainly from enhanced active allocation with higher beta exposure [13]. The bear market environment (2022) shows a completely different picture, with risk parity and minimum variance optimization outperforming, with a downside Beta of only 0.76, effectively controlling portfolio losses. A side-by-side comparison reveals that during periods of high volatility (average volatility >20%), the optimization algorithm with machine learning elements shows greater resilience, with average retracements reduced by 37% compared to the traditional approach. During the liquidity crisis session (April 2023), the hybrid optimization strategy that takes into account transaction costs outperforms, with 6.2 percentage points less NAV retraction than the optimization that does not take liquidity into account. Correlation analysis shows that optimization algorithm performance exhibits a non-linear relationship with the VIX Panic Index, with dynamic optimization strategies generating the highest excess returns in moderate market volatility (15-25) environments, while simple diversification strategies are instead more defensively effective in extreme low- or high-volatility markets.

### 4.3. Typical Case Studies

The impact of optimization algorithms in fund performance can be evidenced by both positive and negative typical cases. In the successful case, a leading quantitative fund has increased its asset size by more than five times after introducing the multi-objective optimization framework, with a three-year cumulative return of 74.3%, significantly outperforming its benchmark. Its success stems from the value of three algorithms: dynamic factor rotation to capture style switching, non-linear factor optimization to enhance stock selection, and CVaR constraints to effectively control retracement. In contrast to the failure case, a medium-sized fund met its Waterloo after adopting a complex deep learning framework, which deteriorated dramatically from the initial bright performance to the market style shift. Lessons learned from the failure include model overfitting, frequent adjustments leading to excessive turnover, lack of stop-loss mechanism and poor human-machine collaboration [14]. The comparison of the two cases highlights the key factors to optimize the application of algorithms: maintaining moderate complexity, establishing complete multi-scenario testing, establishing effective risk warning and human-machine collaborative decision-making mechanisms.

## 5. DISCUSSION OF LIMITATIONS OF ALGORITHMIC OPTIMIZATION

### 5.1. Model Risk Analysis

Portfolio optimization algorithms face significant model risk challenges, mainly in the three aspects of parameter sensitivity, estimation error and overfitting. The optimization model is highly sensitive to the input parameters, and small parameter changes may lead to large fluctuations in portfolio weights, making the optimal solution unstable in practice. Estimation errors in return, volatility and correlation forecasts are magnified in the optimization process, leading to significant deviations of the actual risk-return characteristics from the target [15]. The overfitting problem is particularly severe in complex models and manifests itself in large differences between in-sample and out-of-sample performance. This model risk is even more pronounced when markets undergo structural changes, especially for complex optimization models such as deep learning, which often do not adapt as well as expected to changes in the environment [16]. Large portfolios face the problem of “dimensional catastrophe”, where the cumulative effect of estimation errors is multiplied by the increase in the number of assets, which significantly reduces the reliability of the optimization results.

### 5.2. Market Shocks and Transitivity Problems

Market shocks and contrarian issues arising from the widespread use of optimization algorithms are becoming increasingly prominent. Homogenized optimization methods lead to the convergence of institutional investors' positions, creating trading congestion, which often triggers liquidity crises and sharp price fluctuations at market turning points. This algorithmic convergence leads to an accelerated decay in the validity of investment signals and a significant reduction in the half-life of strategies, creating an arms race in which optimization algorithms are constantly chasing new signals. Market contrarianism is manifested in the interaction between optimization algorithms [17-18]. When a large number of algorithms based on similar logic respond to market changes at the same time, what was originally a small fluctuation may be amplified into significant market volatility. Liquidity risk is particularly prominent in the process of algorithmic position-taking, with price shocks arising from concentrated trading in certain assets far exceeding the expectations of traditional risk models. Even more challenging is the unpredictability of the complex systematic effects generated by algorithmic interactions. Extreme events such as flash crashes have a low probability of occurring but have far-reaching impacts, and traditional risk management frameworks are limited in their ability to prevent such events.

### **5.3. Regulatory Compliance and Ethical Challenges**

Portfolio optimization algorithms face multiple challenges in terms of regulatory compliance and ethics. Transparency is the most prominent, as complex algorithms are often viewed as “black boxes”, making it difficult for investors to understand their decision-making logic and creating significant information asymmetries. This has led to increased scrutiny of algorithmic trading by regulators, who require traceability of decision-making. Liability disputes are another key issue, with blurred liability boundaries between fund managers, algorithm developers and investors triggering legal disputes when algorithmic decisions lead to significant losses [19-20]. The fairness challenge is reflected in the issue of algorithmic preference. Mainstream optimization models have systematic preferences for specific types of assets, which may exacerbate market divergence and affect the price discovery function of the capital market. Arbitrage strategies generated by the combination of high-frequency trading and algorithmic optimization consume a large amount of market resources but make limited contribution to price discovery, triggering disputes over the fairness of market resource allocation. As the influence of algorithms in investment decision-making increases, how to balance technological innovation and risk control, and how to build an ethical framework and regulatory mechanism adapted to the era of algorithms has become a major issue for academics and regulators.

## **6. CONCLUSIONS AND RECOMMENDATIONS**

This study provides an in-depth analysis of the mechanisms and empirical effects of portfolio optimization algorithms on fund performance. It is found that optimization algorithms significantly affect fund performance in terms of return enhancement, risk control and cost management, but the effects are moderated by market environment and algorithm type. Machine learning and hybrid optimization strategies show better risk-adjusted returns in most market environments, but traditional algorithms remain useful in stable markets. To address the practice, it is recommended that fund managers build a multi-scenario testing framework to assess algorithmic robustness; adopt a multi-objective optimization methodology that balances return, risk and cost; establish an effective risk monitoring mechanism for the model; balance algorithmic complexity and interpretability; and maintain the collaboration between algorithms and human judgment to complement each other. The regulatory level should strengthen the transparency requirements of algorithmic transactions, prevent the accumulation of systemic risks, and build an algorithmic regulatory sandbox to promote innovation.

## **7. FUTURE RESEARCH DIRECTIONS**

Future research can expand the research boundary of portfolio optimization algorithms in multiple dimensions. Deeply explore the application value of nonconvex optimization in the nonlinear structure of financial markets, especially the robustness performance in extreme market environments. Incorporate investor behavioral bias into the optimization framework, construct models that are more in line with the real decision-making process, and bridge the gap between theory and practice. Explore the potential of blockchain and smart contracts in optimizing the execution of solutions to enhance trading efficiency and transparency. Develop an integrated optimization methodology across markets and multiple asset classes to respond to globalized investment needs. Investigate the integration path between optimization algorithms and ESG objectives to balance financial performance and sustainability requirements. Analyze in-depth market microstructure changes under algorithmic interactions, and construct a systematic risk metric framework that considers reflexivity. Explore the application prospect of quantum computing in high-dimensional optimization problems and break through the traditional computational bottleneck. These directions will promote the theory and practice of portfolio optimization to a broader and deeper field.

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