MASS: MULTI-AGENT SIMULATION SCALING FOR PORTFOLIO CONSTRUCTION

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ABSTRACT

The application of LLM-based agents in financial investment has shown significant promise, yet existing approaches often require intermediate steps like predicting individual stock movements or rely on predefined, static workflows. These limitations restrict their adaptability and effectiveness in constructing optimal portfolios. In this paper, we introduce the Multi-Agent Scaling Simulation (MASS), a novel framework that leverages multi-agent simulation for direct, end-to-end portfolio construction. At its core, MASS employs a backward optimization process to dynamically learn the optimal distribution of heterogeneous agents, enabling the system to adapt to evolving market regimes. A key finding enabled by our framework is the exploration of the scaling effect for portfolio construction: we demonstrate that as the number of agents increases exponentially (up to 512), the aggregated decisions yield progressively higher excess returns. Extensive experiments on a challenging, self-collected dataset from the 2023 Chinese A-share market show that MASS consistently outperforms seven state-of-the-art baselines. Further backtesting, stability analyses and the experiment on data leakage concerns validate its enhanced profitability and robustness. We have open-sourced our code, dataset, and training snapshots at https://github.com/gta0804/MASS/ to foster further research.

1 INTRODUCTION

The application of LLM-based agents in investment analysis has recently garnered significant attention from both academia and industry (Tang et al., 2025; Xiao et al., 2025b; Li et al., 2025b). By assigning LLMs with distinct roles and providing them with relevant financial context, researchers have developed agent-based systems to tackle complex tasks such as alpha factor mining (Cao et al., 2025; Li et al., 2025b) and stock trend prediction (Koa et al., 2024; Yu et al., 2024). These pioneering efforts highlight the potential of LLMs to process and reason over vast amounts of multi-modal financial data, including news, reports, and market indicators.

Despite their promise, existing LLM-based approaches in finance exhibit two primary limitations. First, many systems are designed for individual stock forecasting (Koa et al., 2024; Yu et al., 2024; Xiao et al., 2025b). While useful, predicting the movement of single stocks does not directly translate to constructing an optimal portfolio, which requires a holistic assessment of asset correlations, market sentiment, and risk diversification. Second, these systems typically rely on predefined procedural workflows to orchestrate agent interactions (Guo et al., 2024). This reliance on static, pre-programmed processes limits their ability to adapt to the highly dynamic and non-stationary nature of financial markets, potentially compromising their performance during market regime shifts.

In this paper, we introduce the Multi-Agent Scaling Simulation (**MASS**) to address these challenges. MASS shifts the paradigm from individual stock prediction to direct portfolio construction by simulating a market of heterogeneous investor agents. Instead of relying on static workflows, MASS introduces a novel backward optimization process. This mechanism uses historical market data to dynamically learn the optimal distribution of agent types that maximizes portfolio returns, allowing the system to adapt its strategy. This approach provides MASS with three key advantages: (1) It leverages aggregated information from a multi-agent simulation for direct, end-to-end portfolio construction, bypassing intermediate steps like individual stock prediction; (2) It replaces predefined workflows with a data-driven optimization process, enhancing adaptability and performance; and (3) It enables us to explore the multi-agent scaling effect for portfolio construction: as the number of agents increases exponentially, the system's decisions achieve higher excess returns. To the best of our knowledge, MASS is the first work to scale multi-agent simulation for this task up to 512 agents.

To rigorously evaluate MASS, we collected a rather comprehensive and challenging dataset from the Chinese A-share market for the entirety of 2023, a period marked by significant volatility and two major market shifts. Our dataset, covering the *SSE50*, *CSI 300*, and *ChiNext 100* indices, includes detailed firm-level features and macroeconomic indicators. Extensive experiments demonstrate that MASS significantly outperforms seven state-of-the-art baselines. Rigorous backtesting further confirms its ability to generate consistent excess returns with lower drawdowns. To address concerns about data leakage in the LLM (`Qwen-2.5-72B-Instruct`), we validate our findings on new data from the first quarter of 2025. Additional experiments confirm MASS's scalability, stability in dynamic markets, and robustness to hyperparameters, while visualizations of the agent distribution dynamics offer insights into its adaptive mechanism.

In summary, this paper makes the following contributions:

- We introduce MASS, a novel framework leveraging multi-agent simulation with end-to-end backward optimization for decision-making in portfolio construction.
- To our best knowledge, we are the first to explore and demonstrate a scaling effect in multi-agent simulation for portfolio construction, expanding the number of agents up to 512.
- Extensive experiments show that MASS outperforms state-of-the-art baselines, delivering consistent excess returns, scalability, and stability. We also address potential data leakage concerns and validate our simulation's effectiveness through visualization.
- We have introduced and released a comprehensive, realistic, and rich dataset, along with our code and training snapshots, to facilitate future research in this domain.

2 RELATED WORK

This section reviews related work across three key areas to contextualize our research. We first discuss our primary research domain: existing investment analysis approaches within the financial market. We then survey the landscape of LLM-based multi-agent systems, which constitute our methodological approach. Finally, we cover the emerging research on scaling effects for multi-agent systems, a significant finding that informs our understanding of system performance.

2.1 INVESTMENT ANALYSIS

Investment analysis research traditionally focuses on two main tracks: formulaic alpha mining and stock price trend prediction. Alpha mining aims to discover mathematical expressions from financial data that predict future returns, using techniques like genetic algorithms (Chen et al., 2021), deep reinforcement learning (Yu et al., 2023; Shi et al., 2025a), and more recently, LLM-based agents (Tang et al., 2025; Cao et al., 2025; Ding et al., 2025; Li et al., 2025b; Shi et al., 2025b). Stock price trend prediction employs methods ranging from traditional time-series analysis (Choi, 2018) and deep learning models (Yoo et al., 2021; Xu et al., 2021; Luo et al., 2023; Du et al., 2024a; Li et al., 2024a; Yang et al., 2025a; Chen et al., 2025). reinforcement learning models (Niu et al., 2022; Yuan et al., 2025) to the latest LLM-based agents (Koa et al., 2024; Xiao et al., 2025b; Zhang et al., 2024c) and foundation model training (Liu et al., 2025; Xiao et al., 2025a; Shi et al., 2025c). While effective to a degree, alpha mining often treats the market monolithically, overlooking stock-specific idiosyncrasies, while most trend prediction methods focus on individual assets rather than portfolio-level optimization. Furthermore, many recent LLM-agent approaches rely on fixed, predefined workflows, limiting their adaptability. Additionally, LLMs trained on massive historical data introduce the risk of data leakage, as the historical data may encapsulate past market information.

MASS distinguishes itself from these works by shifting the focus from individual stock prediction or factor mining to the direct task of portfolio construction. Unlike methods that rely on predefined workflows, MASS employs a data-driven, end-to-end optimization framework to dynamically infer the underlying distribution of investor archetypes that leads to optimal portfolio performance. This simulation-based approach allows MASS to holistically model market dynamics and adapt to changing conditions, offering superior performance and market adaptability compared to forecasting individual asset movements in isolation.

2.2 LLM-BASED MULTI-AGENT SYSTEMS

LLM-based multi-agent systems (MAS) are broadly classified into two categories: *Simulation* and *Application* (Guo et al., 2024). Simulation-focused MAS are used to model emergent social (Park et al., 2023), economic (Zhao et al., 2024; Li et al., 2023b), or psychological phenomena (Kovac et al., 2023; Zhang et al., 2024b). Their primary goal is to validate existing theories or generate analytical insights. In contrast, Application-focused MAS employ specialized agents organized in structures like layers (Liu et al., 2024) or centralized hierarchies (Qian et al., 2025) to collaboratively execute specific tasks, such as software development (Li et al., 2023a) or scientific debate (Du et al., 2024b). These systems typically follow predefined procedural workflows to ensure efficient coordination.

MASS bridges the gap between these two categories. Compared to existing simulations, which are primarily used for analysis, MASS utilizes the aggregated output of its simulation for concrete, real-world decision-making, thereby expanding the practical boundaries of multi-agent simulation. Unlike existing applications that depend on rigid, predefined processes, MASS leverages a data-driven, end-to-end backward optimization mechanism. This allows the system to learn its own optimal collaborative strategy from market feedback, resulting in superior performance and adaptability without the need for hand-crafted workflows.

2.3 SCALING EFFECTS IN MULTI-AGENT SYSTEMS

The study of scaling effects—predictable performance improvements with increased model size, data, or compute—is a key component of modern LLM research (Kaplan et al., 2020). One notable study explores cooperative scaling effects for various predefined agent architectures (e.g., linear, tree), expanding the agent count up to 64 (Qian et al., 2025). Another recent work (Dang et al., 2025) proposes an evolving orchestration where an RL-trained puppeteer dynamically organizes agents into cost-effective collaboration topologies, enhancing scaling in MAS.

As for scaling effects in MAS on the financial domain, Mars (Li et al., 2025a) investigates the effect of training data scale on the realism of financial market simulations, but focuses on simulating the limited order books given by investors rather than the investors within it. StockAgent (Zhang et al., 2024a) introduces an LLM-driven multi-agent system to simulate investor trading behaviors in an LLM-generated stock market environment in response to external factors and market dynamics. TwinMarket (Yang et al., 2025b) is a novel scalable multi-agent framework leveraging Large Language Models to simulate investor behavior in financial markets through dynamic social networks. These studies either constrain agent interactions to fixed topologies or do not focus on utilizing the simulation results to guide real market investments.

In contrast, MASS introduces and investigates a novel scaling paradigm for multi-agent decision-making. Our scaling effect does not rely on a prescribed form of cooperation. Instead, each agent is given a partial view of the market, and as the number of agents increases, the system's collective awareness of the market grows. The core challenge, which we address via our backward optimization process, is learning how to aggregate this distributed intelligence to achieve a specific real-world objective (i.e., maximizing portfolio returns). MASS is the first work to demonstrate this scaling effect in a financial application, expanding the number of simulated agents to 512 and showing a clear correlation between agent scale and investment performance.

3 METHOD

In this section, we introduce MASS, a novel framework that formulates portfolio construction as a dynamic online learning problem. The core idea is to simulate a market of heterogeneous investor agents and learn to optimally aggregate their diverse decisions. MASS operates in a daily cycle of two key processes: **Forward Propagation**, where agents generate investment signals for the current day, and **Backward Optimization**, which refines the model by learning from the previous day's outcomes. This adaptive loop, illustrated in Figure 1, allows MASS to continuously adjust to evolving market conditions. The overall procedure is formalized in Algorithm A.1.

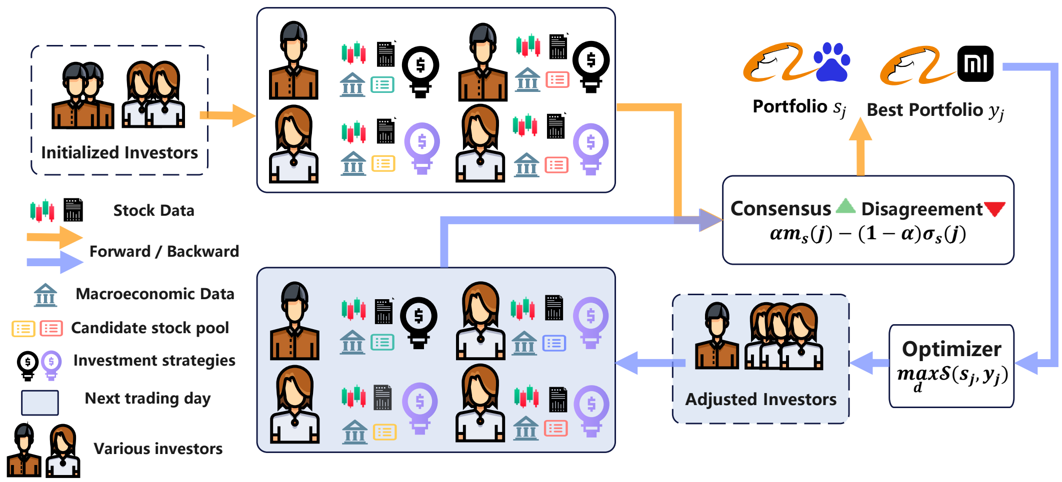

Figure 1: MASS operates in a loop consisting of forward propagation and backward optimization. In the forward propagation, MASS initializes investors using the previous day's investor distribution along with today's stock and macroeconomic data. It then constructs portfolios s_j based on the market disagreement hypothesis. During backward optimization, an optimizer updates the investor distribution, which is then passed to the next trading day.

3.1 FORWARD PROPAGATION

The forward propagation process simulates market activity on a given day j to produce a signal that guides the construction of the portfolio. This involves initializing a diverse population of agents, executing their investment strategies, and aggregating their collective decisions based on a multi-modal stock dataset $\mathcal{X}$.

3.1.1 INVESTOR INITIALIZATION

To capture the diverse perspectives within a real market, MASS initializes a population of $N = n^{\text{type}} \times n^{\text{inv}}$ agents. These agents are categorized into n^{type} distinct types, each embodying a unique investment style (e.g., style outline, risk appetite, rationality). This heterogeneity is crucial for creating a rich and realistic simulation. Each agent type i is provided access to a specific subset of multi-modal data $\mathcal{X}_i \subset \mathcal{X}$. Furthermore, to model the practical constraint that no single investor can monitor the entire market, each individual agent (i, k) is assigned a static, random subset of stocks, denoted as $\text{Pool}(i, k)$, where $|\text{Pool}(i, k)| = n^{\text{sel}}$. This design choice also manages the context length limitations of the underlying LLM. The design details of investor initialization are in Appendix A.3.2.

3.1.2 INVESTMENT STRATEGY EXECUTION

On each trading day j, agents first formulate a daily strategy and then make investment decisions. First, to ensure strategies are adaptive to the prevailing economic climate, each agent type i generates a daily investment strategy by interpreting the latest macroeconomic data $\mathbf{M}_j$ within the context of its intrinsic style. This is performed by an LLM-based function F_1:

$$\text{Strategy}_{i,j} = F_1\left(\text{StyleDesc}_i, \mathbf{M}_j\right) \tag{1}$$

where StyleDesc_i is the textual description of agent type i's investment philosophy.

Next, each agent (i, k) applies this daily strategy to its observable stock universe $\text{Pool}(i, k)$. The agent analyzes the relevant features for these stocks and selects a subset for investment. This decision is modeled by a second LLM-based function F_2:

$$\text{Codes}_{i,k,j} = F_2\Big(\text{Strategy}_{i,j},\ \{\text{data for } s \in \text{Pool}(i,k)\},\ \text{StyleDesc}_i\Big) \tag{2}$$

where $\text{Codes}_{i,k,j} \subseteq \text{Pool}(i,k)$ is the set of stocks selected by agent (i,k) on day j. The design details of this section are provided in Appendix A.3.3.

3.1.3 Score Aggregation

To derive an actionable signal for each stock, we aggregate the decisions from all N agents. Our aggregation strategy is grounded in the market disagreement hypothesis (Miller, 1977; Diether et al., 2002), which posits that stocks with high consensus and low disagreement among investors tend to yield higher future returns. This provides a theoretically sound basis for combining agent outputs. We provide more details about market disagreement hypothesis on Appendix A.3.1.

Let $V_{i,s,j}$ be the fraction of agents of type i that selected stock s on day j. Let $\mathbf{d}_{j-1} = [d_{1,j-1}, \ldots, d_{n^{\text{type}},j-1}]^\top$ be the distribution of agent types, optimized from the previous day. We quantify consensus and disagreement for each stock s by computing the weighted mean (m_s) and weighted standard deviation (σ_s) of selections across all agent types:

$$m_s(j) = \sum_{i=1}^{n^{\text{type}}} d_{i,j-1} \cdot V_{i,s,j} \quad \text{(Consensus)} \tag{3a}$$

$$\sigma_s(j) = \sqrt{\sum_{i=1}^{n^{\text{type}}} d_{i,j-1}(V_{i,s,j} - m_s(j))^2} \quad \text{(Disagreement)} \tag{3b}$$

The final signal for each stock integrates these two components, rewarding consensus and penalizing disagreement:

$$\text{Signal}(s,j) = \alpha \cdot m_s(j) - (1-\alpha) \cdot \sigma_s(j) \tag{4}$$

where $\alpha \in [0,1]$ is a hyperparameter balancing the two effects. This signal is then used to rank stocks and construct the daily portfolio $\mathbf{P}_j$.

3.2 Backward Optimization

A key innovation of MASS is its ability to adapt to changing market regimes. This is achieved through the backward optimization process, which dynamically adjusts the agent type distribution $\mathbf{d}_j$ at the end of each day j. The objective is to find the distribution that would have yielded the best performance over a recent historical window, ensuring the model continuously learns from market feedback.

Specifically, at the end of day j, we define a look-back window[1] of size ω_{opt}. We use the agent decisions $\{V_{i,s,t}\}$ and the actual market returns $\{\mathbf{Y}_t\}$ for the period $t \in [j - \omega_{\text{opt}} + 1, j]$. For any candidate distribution $\mathbf{d}$, we can compute the historical signals $\text{Signal}_{\mathbf{d}}(s,t)$ for this period. The goal is to find the optimal distribution $\mathbf{d}_j$ that maximizes the correlation between these historical signals and the actual returns. This is formulated as an optimization problem:

$$\mathbf{d}_j = \arg\max_{\mathbf{d} \in \Delta^{n^{\text{type}}-1}} \mathcal{S}\left(\{\text{Signal}_{\mathbf{d}}(:,t)\}_{t=j-\omega_{\text{opt}}+1}^{j},\ \{\mathbf{Y}_t\}_{t=j-\omega_{\text{opt}}+1}^{j}\right) \tag{5}$$

where $\Delta^{n^{\text{type}}-1}$ is the probability simplex, and $\mathcal{S}$ is a similarity metric such as the Rank Information Coefficient (RIC). We employ simulated annealing (Kirkpatrick et al., 1983) as the optimizer $\mathcal{O}$ to solve this problem. The resulting distribution $\mathbf{d}_j$ is then carried forward to the next day's forward propagation step (Eq. 3), completing the online learning cycle.

Table 1: Comparisons with baselines and the experiment on data leakage concern. MASS outperforms all others across all 3 stock pools. The best performance in each column is highlighted in **bold**. For more evaluation metrics on portfolio construction, please refer to Appendix A.5.

Method	SSE50				CSI 300				Chi Next 100			
Main Experiments (Throughout 2023)												
	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR
Proxy Indicator (Diether et al., 2002)	3.82	19.73	2.89	16.63	3.84	30.44	3.60	27.03	-0.94	-7.05	0.16	1.29
LightGBM (Ke et al., 2017)	3.25	21.78	4.51	27.30	5.20	36.06	3.19	23.62	2.94	30.69	0.88	8.70
DTML (Yoo et al., 2021)	5.04	28.15	4.93	26.71	4.91	35.72	4.17	31.10	3.45	26.55	3.21	21.97
MASTER (Li et al., 2024b)	5.13	28.37	4.97	27.01	5.01	35.47	4.23	30.78	3.92	31.03	4.07	28.62
SEP (Koa et al., 2024)	4.79	27.56	4.16	26.40	3.83	5.42	0.61	7.65	4.81	34.88	5.29	36.98
FinCON (Yu et al., 2024)	4.88	26.18	4.35	25.67	0.70	9.57	0.96	13.42	5.01	37.18	5.53	40.54
TradingAgents (Xiao et al., 2025b)	4.92	27.71	4.33	25.69	3.01	10.14	1.02	14.80	5.37	38.15	5.60	41.06
MASS	**8.16**	**41.74**	**5.90**	**33.43**	**6.50**	**43.49**	**4.65**	**33.32**	**7.62**	**62.87**	**6.28**	**55.88**
Experiments on data leakage concern (The first quarter of 2025)												
Method	SSE50				CSI 300				CSI A500			
	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR
MASS	4.50	24.41	6.12	38.33	3.91	37.44	3.36	34.56	5.19	56.17	4.66	48.82

4 EVALUATION

Optimization Strategy: We employ simulated annealing (Kirkpatrick et al., 1983) as the optimizer in our backward optimization process to align the investor distribution with optimal market portfolios.

Complexity: Although the total time complexity for a historical simulation is $O(n_{\text{type}} \times n_{\text{inv}} \times T)$, in a live trading scenario, the daily cost is only $O(n_{\text{type}} \times n_{\text{inv}})$. This is because we can store the latest agent distribution snapshot and update it with the newly arriving data stream. To ensure MASS's reproductivity, a detailed analysis of time and computational costs is provided in Appendix A.3.4.

Dataset and Stock Pools: While prior studies Koa et al. (2024); Zhang et al. (2024c); Xiao et al. (2025b) provide valuable insights, their evaluations often focus on US markets during stable bull periods Nasdaq (2025). To test model robustness in a more volatile context, and lacking a comparable multimodal US dataset, we introduce a new dataset from the Chinese A-share market. Our dataset covers the entirety of 2023, a period marked by high volatility and two major shifts, thus offering a challenging benchmark. To foster further research, we have open-sourced one of our dataset. The data covers three key indices: *SSE 50* (China Securities Index Co., 2020), *CSI 300* (China Securities Index Co., 2023), and *ChiNext 100* (Shenzhen Securities Information Co., 2019). For each stock, the dataset includes news, financial reports, price-volume features, and fundamental data, complemented by macroeconomic indicators. Details about the construction of our dataset are in Appendix A.2.

Baselines: We compare MASS with various baselines across different categories: a traditional proxy indicator (Diether et al., 2002); a machine learning model, LightGBM (Ke et al., 2017); deep learning models, DTML (Yoo et al., 2021) and MASTER (Li et al., 2024b); and three SOTA agent-based methods, SEP (Koa et al., 2024), FINCON (Yu et al., 2024), and TradingAgents (Xiao et al., 2025b). While Mars (Li et al., 2025a) is relevant, a direct comparison is not possible because their model weights are still under review [2]. Further details about baseline descriptions and our implementations are in Appendix A.4.

Metrics: We use four standard metrics to assess both correlation and consistency: the Information Coefficient (IC) and Rank Information Coefficient (RIC) quantify Pearson and Spearman correlations between predicted ($Signal$) and actual returns (r), respectively. Their stability is measured by the Information Coefficient Information Ratio (ICIR) and Rank Information Coefficient Information Ratio (RICIR), defined as $\mathbb{E}[\text{IC}]/\text{Std}(\text{IC})$ and $\mathbb{E}[\text{RIC}]/\text{Std}(\text{RIC})$. Besides, to ensure the robustness of our evaluation process, we incorporate more metrics on Appendix A.5.

Experiment-Specific Settings: We utilize *Qwen2.5 72B Instruct* (Qwen et al., 2025) to implement MASS. For the Main Experiments (Table 1), we set $n^{\text{type}} = 16$ and $n^{\text{inv}} = 32$. For SSE 50 and

[1]To avoid inadvertent use of future information, $\mathbf{Y}^k[:, j-k]$ is excluded, because this label depends on the first 15 minutes on day $j+1$ and latency in live trading systems should be considered.

[2] `https://github.com/microsoft/MarS`

ChiNext 100, n^{sel} is 20; for the larger CSI 300, it is 30. We set $\alpha = 0.5$ for SSE 50 and CSI 300. For ChiNext 100, we use $\alpha = 0.2$, reflecting that for China's growth market, where valuations are often disconnected from fundamentals, disagreement factors (σ_s) are more predictive than consensus factors (m_s).For the backward optimization process, we employ simulated annealing (SA) (Kirkpatrick et al., 1983). The key hyperparameters are configured as follows: an initial temperature of 40, a maximum of 100 iterations, and a cooling rate of 0.95. The optimizer look-back window ω_{opt} is set to 5. For the Data Leakage Experiments (Table 1), we used `Qwen2.5-72B-Instruct` (released Sept. 2024) and evaluated it on data from Q1 2025 across SSE 50, CSI 300, and the new CSI A500 index (China Securities Index Co., 2024). For other experiments, we primarily used the CSI 300 pool due to its size and popularity, unless specified otherwise.

4.1 Results and Analysis

4.1.1 Main Experiments

Table 1 presents the primary comparison against baselines. The key observations are twofold. First, MASS achieves the best performance across all metrics and stock pools, consistently outperforming the next-best methods (TradingAgents, SEP, FinCON and MASTER). Second, we observe that while agent-based methods like SEP and FINCON perform reasonably on smaller pools, their effectiveness diminishes significantly on the larger CSI 300. Our analysis indicates this is because their self-reflection mechanisms, which require processing extensive historical results in-context, face comprehension and decision-making challenges with an increasing number of stocks. MASS avoids this bottleneck as its architecture does not require any single agent to process vast global information, demonstrating superior scalability.

4.1.2 Experiments on data leakage concern

To confirm that MASS's performance is not merely a result of the LLM memorizing 2023 market data, we conducted rigorous tests on unseen data. As shown in the lower part of Table 1, MASS maintains significant effectiveness on both unseen data from existing indices (SSE 50, CSI 300 in Q1 2025) and on a completely new stock pool (CSI A500). This result provides strong evidence that the model's success stems from its methodological framework rather than prior knowledge.

4.1.3 Backtesting Experiments

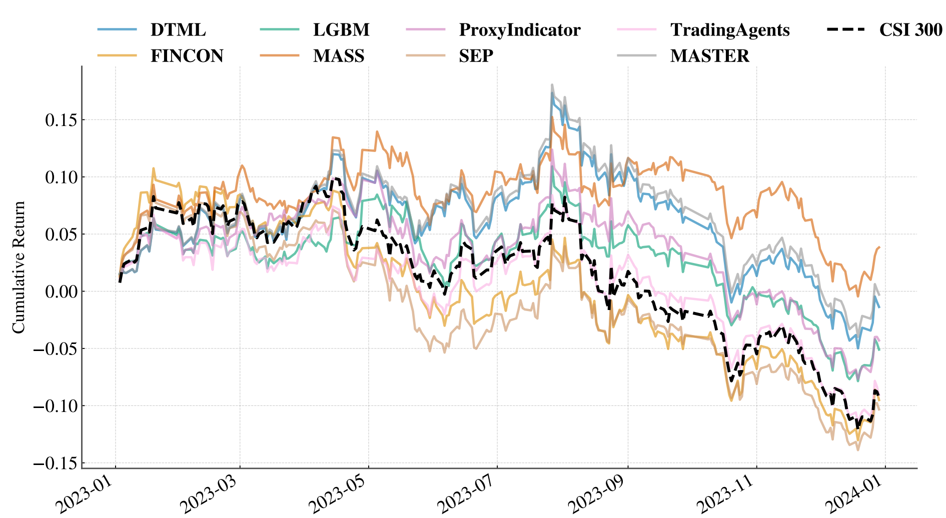

Figure 2: Backtesting on the CSI 300 Stock Pool compared with Baselines and the CSI 300 Index.

Figure 2 translates the statistical metrics into a practical financial outcome via backtesting. The plot of cumulative excess returns shows that MASS not only generates substantially higher returns than the baselines and the CSI 300 index but also maintains significantly lower drawdowns. This result highlights MASS's dual advantages in both profitability and risk control, underscoring its real-world applicability. Backtesting implementation details are in Appendix A.6.

4.1.4 SCALING EXPERIMENTS

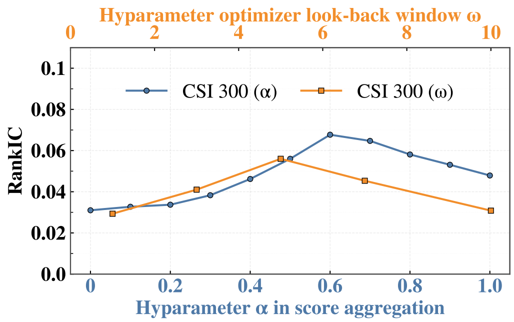

Figure 3: MASS exhibits a moderate sensitivity to changes in hyperparameters.

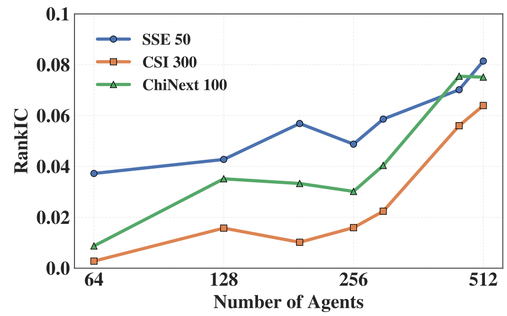

Figure 4: As the number of agents increases exponentially, MASS is able to obtain even more refined market information.

To verify the multi-agent scaling effect, we investigated the performance of MASS as we exponentially increased the number of agents ($n^{\text{type}} \times n^{\text{inv}}$) while keeping other parameters fixed. The results in Figure 4 show a clear, approximately linear growth in the RankIC metric as the total number of agents increases. This confirms that by simulating more agents, MASS is able to capture more refined market information, leading to better investment decisions. To the best of our knowledge, we are the first to explore this scaling effect in multi-agent simulation for portfolio construction, expanding the agent count up to 512.

4.1.5 ABLATION STUDIES

Table 2: Ablation study results for CSP, PMD, BO, MDH, and an investigation of MASS , which daily updates the candidate stock pool, called MASS(DU). The best performance is indicated in **bold**. The EMCL refers to the inability to operate when exceeding the maximum context length of the LLM.

Method	SSE 50				CSI 300				Chi Next 100			
	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR	RIC	RICIR	IC	ICIR
w/o CSP	1.65	11.19	1.67	11.73	EMCL				EMCL			
w/o PMD	5.25	29.75	3.43	21.10	2.57	33.38	2.23	30.64	2.26	17.16	2.99	22.70
w/o BO	0.76	4.75	-0.13	-8.44	0.36	5.36	0.41	6.69	2.88	19.43	3.12	22.03
w/o MDH	6.28	32.68	3.85	25.39	4.65	31.03	2.98	27.86	-3.12	-28.93	-2.46	-26.44
MASS(DU)	8.03	41.68	5.79	**33.52**	6.48	42.86	4.52	32.95	**7.65**	**63.02**	**6.29**	**55.91**
MASS	**8.16**	**41.74**	**5.90**	33.43	**6.50**	**43.49**	**4.65**	**33.32**	7.62	62.87	6.28	55.88

Table 2 presents the results of ablating four key design choices and our variant of our proposed MASS:

- **w/o CSP (Candidate Stock Pool):** Removing this component causes the model to fail on larger indices due to exceeding the LLM's context length (EMCL). This confirms that CSP is essential for the system's scalability.
- **w/o PMD (Provide Macro Data):** Removing macroeconomic data leads to a significant performance drop, as agents lack the context to make diverse, timely decisions, thus reducing system randomness and adaptability.
- **w/o BO (Backward Optimization):** This is the most critical ablation study. Disabling the optimization process in Equation 5 causes performance to collapse, yielding near-zero or negative IC values. This proves that the end-to-end, adaptive learning of agent distribution is the core mechanism driving MASS's success.

- **w/o MDH (Market Disagreement Hypothesis):** Relying solely on consensus led to a major performance drop and was even counterproductive on the ChiNext index, demonstrating the importance of our theory-grounded aggregation method.

- **MASS(DU) (Daily Updated Candidate Stock Pool)**:In Section 3.1.1, we construct each agents' a static candidate stock pool. To confirm the robustness of MASS and eliminate the possible impact of this pre-defined set, we also test a variant which updates each agent's candidate stock pool on each trading day, finding its impact negligible. This suggests that the key is the partitioned view, not whether the view is static or dynamic.

4.1.6 STABILITY AND AGENT DISTRIBUTION VISUALIZATION EXPERIMENT

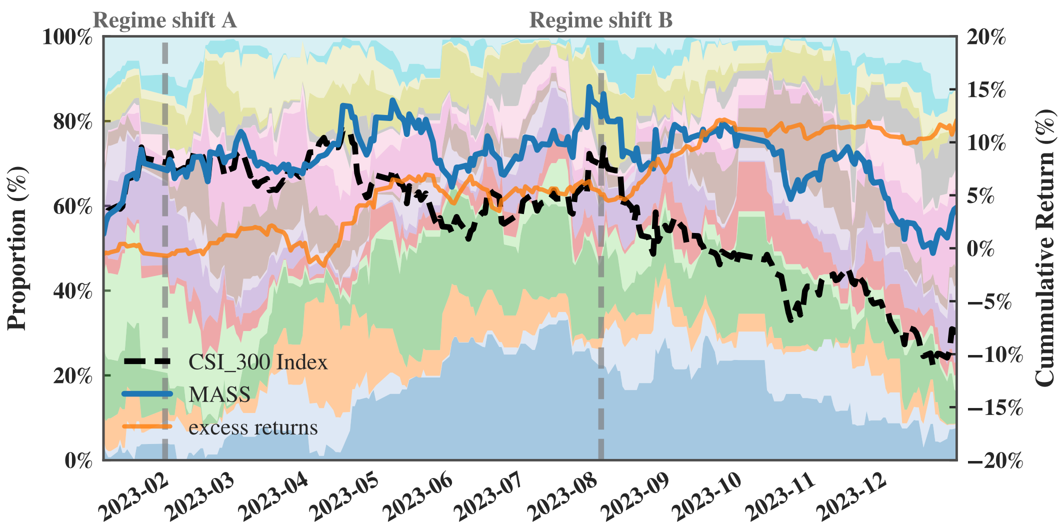

Figure 5: The distribution of agents in MASS swiftly adapts to changes in market styles (A and B), allowing it to consistently achieve stable excess returns compared to the CSI 300 Index.

Figure 5 provides a visual proof of MASS's adaptability. The background color tracks the temporal evolution of the agent distribution throughout 2023, with the left y-axis representing the proportion of different agent types. The right y-axis indicates the cumulative return, which is used to plot the performance of our MASS (blue line) and the CSI 300 Index (black dashed line). The orange line illustrates the excess cumulative return of MASS compared to the CSI 300 benchmark. The two major market shifts in February (rebound to consolidation) and August (consolidation to decline) are marked as A and B. It is evident that during both transitions, MASS's backward optimization mechanism swiftly adapted the agent distribution to align with the new market style. This rapid adaptation enabled MASS to consistently achieve stable excess returns compared to the CSI 300 index, even during periods of high volatility.

4.1.7 PARAMETER SENSITIVITY EXPERIMENTS

To investigate the sensitivity of MASS to its parameters, we analyzed two hyperparameters: the score aggregation weight α (Equation 4) and the optimizer look-back window ω_{opt}. The parameter α manages the balance between disagreement and consensus components in portfolio construction, while ω_{opt} influences information capacity—too short a window limits it, whereas too long a duration hinders regime adaptation. The experimental results are presented in Figure 3.

We observe that although adjustments to these two hyperparameters lead to slight variations in system performance, these changes are within acceptable limits. This indicates that MASS exhibits a moderate sensitivity to parameter changes.

5 Conclusion

In this paper, we introduce MASS, a multi-agent scaling simulation framework designed for portfolio construction. MASS leverages large-scale agent simulations and a backward optimization process to achieve a comprehensive understanding of market dynamics. This approach offers various advantages, including enhanced scalability, robustness, and the ability to generate stable excess returns.

In the future, we anticipate that the paradigm established by MASS will extend beyond investment portfolio management to encompass a wider range of tasks, such as supply chain optimization, agricultural decision-making, and weather prediction.

References

Turan G Bali, Bryan T Kelly, Mathis Mörke, and Jamil Rahman. Machine forecast disagreement. Working Paper 31583, National Bureau of Economic Research, August 2023. URL http://www.nber.org/papers/w31583.

Lang Cao, Zekun Xi, Long Liao, Ziwei Yang, and Zheng Cao. Chain-of-alpha: Unleashing the power of large language models for alpha mining in quantitative trading. *arXiv preprint arXiv:2508.06312*, 2025.

Tianxiang Chen, Wei Chen, and Luyao Du. An empirical study of financial factor mining based on gene expression programming. In *2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE)*, pp. 1113–1117. IEEE, 2021.

Weijun Chen, Shun Li, Heyuan Wang, and Tengjiao Wang. Enhancer: A distribution-aware framework with temporal-relational meta-learning for stock prediction. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pp. 250–261, 2025.

Ltd China Securities Index Co. *Compilation of the SSE 50 Index*, 2020. URL https://oss-ch.csindex.com.cn/static/html/csindex/public/uploads/indices/detail/files/zh_CN/000016_Index_Methodology_cn.pdf.

Ltd China Securities Index Co. *Compilation of the CSI 300 Index*, 2023. URL https://oss-ch.csindex.com.cn/static/html/csindex/public/uploads/indices/detail/files/zh_CN/000300_Index_Methodology_cn.pdf.

Ltd China Securities Index Co. *Compilation of the CSIA500 Index*, 2024. URL https://oss-ch.csindex.com.cn/static/html/csindex/public/uploads/indices/detail/files/zh_CN/000510_Index_Methodology_cn.pdf.

Hyeong Kyu Choi. Stock price correlation coefficient prediction with arima-lstm hybrid model, 2018. URL https://arxiv.org/abs/1808.01560.

Yufan Dang, Chen Qian, Xueheng Luo, Jingru Fan, Zihao Xie, Ruijie Shi, Weize Chen, Cheng Yang, Xiaoyin Che, Ye Tian, et al. Multi-agent collaboration via evolving orchestration. In *The Thirty-ninth Annual Conference on Neural Information Processing Systems*, 2025.

Karl B Diether, Christopher J Malloy, and Anna Scherbina. Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5):2113–2141, 2002. doi: 10.1111/0022-1082.00490.

Hongjun Ding, Binqi Chen, Jinsheng Huang, Taian Guo, Zhengyang Mao, Guoyi Shao, Lutong Zou, Luchen Liu, and Ming Zhang. Alphaeval: A comprehensive and efficient evaluation framework for formula alpha mining. *arXiv preprint arXiv:2508.13174*, 2025.

Kelvin Du, Rui Mao, Frank Xing, and Erik Cambria. Explainable stock price movement prediction using contrastive learning. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, CIKM '24, pp. 529–537, New York, NY, USA, 2024a. Association for Computing Machinery. ISBN 9798400704369. doi: 10.1145/3627673.3679544. URL https://doi.org/10.1145/3627673.3679544.

Yilun Du, Shuang Li, Antonio Torralba, Joshua B. Tenenbaum, and Igor Mordatch. Improving factuality and reasoning in language models through multiagent debate. In *Proceedings of the 41st International Conference on Machine Learning*, ICML'24. JMLR.org, 2024b.

Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V. Chawla, Olaf Wiest, and Xiangliang Zhang. Large language model based multi-agents: A survey of progress and challenges. In Kate Larson (ed.), *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI-24*, pp. 8048–8057. International Joint Conferences on Artificial Intelligence Organization, 8 2024. doi: 10.24963/ijcai.2024/890. URL `https://doi.org/10.24963/ijcai.2024/890`. Survey Track.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models, 2020. URL `https://arxiv.org/abs/2001.08361`.

Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: a highly efficient gradient boosting decision tree. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, pp. 3149–3157, Red Hook, NY, USA, 2017. Curran Associates Inc. ISBN 9781510860964.

Scott Kirkpatrick, C Daniel Gelatt, and Mario P Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, 1983.

K. J. L. Koa et al. Learning to generate explainable stock predictions using self-reflective large language models. In *Proceedings of the ACM Web Conference (WWW)*, 2024. doi: 10.1145/3589334.3645611. URL `https://dl.acm.org/doi/10.1145/3589334.3645611`.

Grgur Kovac, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer. The socialAI school: Insights from developmental psychology towards artificial socio-cultural agents. In *First Workshop on Theory of Mind in Communicating Agents*, 2023. URL `https://openreview.net/forum?id=Y5r8Wa67Ob`.

Guohao Li, Hasan Abed Al Kader Hammoud, Hani Itani, Dmitrii Khizbullin, and Bernard Ghanem. Camel: communicative agents for "mind" exploration of large language model society. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*, NIPS '23, Red Hook, NY, USA, 2023a. Curran Associates Inc.

Junjie Li, Yang Liu, Weiqing Liu, Shikai Fang, Lewen Wang, Chang Xu, and Jiang Bian. Mars: a financial market simulation engine powered by generative foundation model. In *The Thirteenth International Conference on Learning Representations*, 2025a. URL `https://openreview.net/forum?id=Yqk7EyT52H`.

Shuqi Li, Yuebo Sun, Yuxin Lin, Xin Gao, Shuo Shang, and Rui Yan. Causalstock: Deep end-to-end causal discovery for news-driven multi-stock movement prediction. In A. Globerson, L. Mackey, D. Belgrave, A. Fan, U. Paquet, J. Tomczak, and C. Zhang (eds.), *Advances in Neural Information Processing Systems*, volume 37, pp. 47432–47454. Curran Associates, Inc., 2024a. URL `https://proceedings.neurips.cc/paper_files/paper/2024/file/54d689d58fe54c92aee2d732fc49fca8-Paper-Conference.pdf`.

Tong Li, Zhaoyang Liu, Yanyan Shen, Xue Wang, Haokun Chen, and Sen Huang. Master: Market-guided stock transformer for stock price forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 162–170, 2024b.

Yang Li, Yangyang Yu, Haohang Li, Zhi Chen, and Khaldoun Khashanah. Tradinggpt: Multi-agent system with layered memory and distinct characters for enhanced financial trading performance. *arXiv preprint arXiv:2309.03736*, 2023b.

Yuante Li, Xu Yang, Xiao Yang, Minrui Xu, Xisen Wang, Weiqing Liu, and Jiang Bian. R&d-agent-quant: A multi-agent framework for data-centric factors and model joint optimization. In *The Thirty-ninth Annual Conference on Neural Information Processing Systems*, 2025b.

Zhaowei Liu, Xin Guo, Fangqi Lou, Lingfeng Zeng, Jinyi Niu, Zixuan Wang, Jiajie Xu, Weige Cai, Ziwei Yang, Xueqian Zhao, Chao Li, Sheng Xu, Dezhi Chen, Yun Chen, Zuo Bai, and Liwen Zhang. Fin-r1: A large language model for financial reasoning through reinforcement learning, 2025. URL https://arxiv.org/abs/2503.16252.

Zijun Liu, Yanzhe Zhang, Peng Li, Yang Liu, and Diyi Yang. A dynamic llm-powered agent network for task-oriented agent collaboration. In *First Conference on Language Modeling*, 2024.

Di Luo, Weiheng Liao, Shuqi Li, Xin Cheng, and Rui Yan. Causality-guided multi-memory interaction network for multivariate stock price movement prediction. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 12164–12176, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.679. URL https://aclanthology.org/2023.acl-long.679/.

Edward M Miller. Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, 32(4): 1151–1168, 1977. doi: 10.1111/j.1540-6261.1977.tb03317.x.

Inc. Nasdaq. *NASDAQ-100 Index*, 2025. URL https://www.nasdaq.com/market-activity/index/ndx.

Hui Niu, Siyuan Li, and Jian Li. Metatrader: An reinforcement learning approach integrating diverse policies for portfolio optimization. In *Proceedings of the 31st ACM international conference on information & knowledge management*, pp. 1573–1583, 2022.

Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, UIST '23, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400701320. doi: 10.1145/3586183.3606763. URL https://doi.org/10.1145/3586183.3606763.

Chen Qian, Zihao Xie, YiFei Wang, Wei Liu, Kunlun Zhu, Hanchen Xia, Yufan Dang, Zhuoyun Du, Weize Chen, Cheng Yang, Zhiyuan Liu, and Maosong Sun. Scaling large language model-based multi-agent collaboration. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=K3n5jPkrU6.

Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025. URL https://arxiv.org/abs/2412.15115.

Ronnie Sadka and Anna Scherbina. Analyst disagreement, mispricing, and liquidity. *The Journal of Finance*, 62(5):2367–2403, 2007. doi: 10.1111/j.1540-6261.2007.01278.x.

Ltd Shenzhen Securities Information Co. *Compilation of the ChixNext 100 Index*, 2019. URL https://www.szse.cn/marketServices/message/index/project/P020190201583986359118.pdf.

Hao Shi, Weili Song, Xinting Zhang, Jiahe Shi, Cuicui Luo, Xiang Ao, Hamid Arian, and Luis Angel Seco. Alphaforge: A framework to mine and dynamically combine formulaic alpha factors. In Toby Walsh, Julie Shah, and Zico Kolter (eds.), *AAAI-25, Sponsored by the Association for the Advancement of Artificial Intelligence, February 25 - March 4, 2025, Philadelphia, PA, USA*, pp. 12524–12532. AAAI Press, 2025a. doi: 10.1609/AAAI.V39I12.33365. URL https://doi.org/10.1609/aaai.v39i12.33365.

Yu Shi, Yitong Duan, and Jian Li. Navigating the alpha jungle: An llm-powered mcts framework for formulaic factor mining. *arXiv preprint arXiv:2505.11122*, 2025b.

Yu Shi, Zongliang Fu, Shuo Chen, Bohan Zhao, Wei Xu, Changshui Zhang, and Jian Li. Kronos: A foundation model for the language of financial markets. *arXiv preprint arXiv:2508.02739*, 2025c.

Ziyi Tang, Zechuan Chen, Jiarui Yang, Jiayao Mai, Yongsen Zheng, Keze Wang, Jinrui Chen, and Liang Lin. Alphaagent: Llm-driven alpha mining with regularized exploration to counteract alpha decay. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pp. 2813–2822, 2025.

Yijia Xiao, Edward Sun, Tong Chen, Fang Wu, Di Luo, and Wei Wang. Trading-r1: Financial trading with llm reasoning via reinforcement learning, 2025a. URL https://arxiv.org/abs/2509.11420.

Yijia Xiao, Edward Sun, Di Luo, and Wei Wang. Tradingagents: Multi-agents LLM financial trading framework. In *The First MARW: Multi-Agent AI in the Real World Workshop at AAAI 2025*, 2025b. URL https://openreview.net/forum?id=4QPrXwMQt1.

Wentao Xu, Weiqing Liu, Lewen Wang, Yingce Xia, Jiang Bian, Jian Yin, and Tie-Yan Liu. Hist: A graph-based framework for stock trend forecasting via mining concept-oriented shared information. *arXiv preprint arXiv:2110.13716*, 2021.

Chen Yang, Jingyuan Wang, Xiaohan Jiang, and Junjie Wu. Learning universal multi-level market irrationality factors to improve stock return forecasting. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V.1*, KDD '25, pp. 1739–1750, New York, NY, USA, 2025a. Association for Computing Machinery. ISBN 9798400712456. doi: 10.1145/3690624.3709328. URL https://doi.org/10.1145/3690624.3709328.

Xiao Yang, Weiqing Liu, Dong Zhou, Jiang Bian, and Tie-Yan Liu. Qlib: An ai-oriented quantitative investment platform. *arXiv preprint arXiv:2009.11189*, 2020.

Yuzhe Yang, Yifei Zhang, Minghao Wu, Kaidi Zhang, Yunmiao Zhang, Honghai Yu, Yan Hu, and Benyou Wang. Twinmarket: A scalable behavioral and social simulation for financial markets. In *The Thirty-ninth Annual Conference on Neural Information Processing Systems*, 2025b.

Jaemin Yoo, Yejun Soun, Yong-chan Park, and U Kang. Accurate multivariate stock movement prediction via data-axis transformer with multi-level contexts. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, KDD '21, pp. 2037–2045, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450383325. doi: 10.1145/3447548.3467297. URL https://doi.org/10.1145/3447548.3467297.

Shuo Yu, Hongyan Xue, Xiang Ao, Feiyang Pan, Jia He, Dandan Tu, and Qing He. Generating synergistic formulaic alpha collections via reinforcement learning. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 2023. doi: 10.1145/3580305.3599831.

Yangyang Yu, Zhiyuan Yao, Haohang Li, Zhiyang Deng, Yuechen Jiang, Yupeng Cao, Zhi Chen, Jordan W. Suchow, Zhenyu Cui, Rong Liu, Zhaozhuo Xu, Denghui Zhang, Koduvayur Subbalakshmi, GUOJUN XIONG, Yueru He, Jimin Huang, Dong Li, and Qianqian Xie. Fincon: A synthesized LLM multi-agent system with conceptual verbal reinforcement for enhanced financial decision making. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL https://openreview.net/forum?id=dG1HwKMYbC.

Haochen Yuan, Minting Pan, Yunbo Wang, Siyu Gao, Philip S. Yu, and Xiaokang Yang. Your offline policy is not trustworthy: Bilevel reinforcement learning for sequential portfolio optimization, 2025. URL https://arxiv.org/abs/2505.12759.

Chong Zhang, Xinyi Liu, Zhongmou Zhang, Mingyu Jin, Lingyao Li, Zhenting Wang, Wenyue Hua, Dong Shu, Suiyuan Zhu, Xiaobo Jin, Sujian Li, Mengnan Du, and Yongfeng Zhang. When ai meets finance (stockagent): Large language model-based stock trading in simulated real-world environments, 2024a. URL https://arxiv.org/abs/2407.18957.

Jintian Zhang, Xin Xu, Ningyu Zhang, Ruibo Liu, Bryan Hooi, and Shumin Deng. Exploring collaboration mechanisms for LLM agents: A social psychology view. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 14544–14607, Bangkok, Thailand, August 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.782. URL https://aclanthology.org/2024.acl-long.782/.

Wentao Zhang, Lingxuan Zhao, Haochong Xia, Shuo Sun, Jiaze Sun, Molei Qin, Xinyi Li, Yuqing Zhao, Yilei Zhao, Xinyu Cai, Longtao Zheng, Xinrun Wang, and Bo An. A multimodal foundation agent for financial trading: Tool-augmented, diversified, and generalist. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, KDD '24, pp. 4314–4325, New York, NY, USA, 2024c. Association for Computing Machinery. ISBN 9798400704901. doi: 10.1145/3637528.3671801. URL `https://doi.org/10.1145/3637528.3671801`.

Qinlin Zhao, Jindong Wang, Yixuan Zhang, Yiqiao Jin, Kaijie Zhu, Hao Chen, and Xing Xie. Competeai: understanding the competition dynamics of large language model-based agents. In *Proceedings of the 41st International Conference on Machine Learning*, ICML'24. JMLR.org, 2024.

A Appendix

A.1 High-Level workflow of Mass

Algorithm 1: Mass: Online Learning Framework

Input: Multi-modal stock features $\mathcal{X}$, macroeconomic data $\mathcal{M}$, historical stock returns $\mathbf{Y}$, number of agent types n^{type}, agents per type n^{inv}, look-back window ω_{opt}, trading days T

Output: Daily investment portfolio $\mathbf{P}$

Initialize agent type distribution $\mathbf{d}_0 \leftarrow [\frac{1}{n^{\text{type}}}, \dots, \frac{1}{n^{\text{type}}}]^\top$;
; `// Uniform initial distribution`

Initialize all agents (i, k) for $i \in \{1, \dots, n^{\text{type}}\}$, $k \in \{1, \dots, n^{\text{inv}}\}$;

for *each trading date* $j \in T$ **do**

  `// - Forward Propagation: Generate signal for day j -`

  for *agent type* $i = 1$ **to** n^{type} **do**

    for *agent* $k = 1$ **to** n^{inv} **do**

      Generate investment strategy Strategy$_{i,j}$ using Eq. 1;

      Agent (i, k) selects stocks Codes$_{i,k,j}$ via Eq. 2;

  Aggregate agent decisions to compute $\text{Signal}(s, j)$ for all stocks s via Eqs. 3, 4 using distribution $\mathbf{d}_{j-1}$;

  `// - Portfolio Construction for day j -`

  Construct portfolio $\mathbf{P}_j$ from $\text{Signal}(:, j)$ using a Top-k strategy;

  `// - Backward Optimization: Update distribution for day j+1 -`

  Optimize distribution $\mathbf{d}_j$ using historical data up to day j via Eq. 5;

return *Sequence of daily portfolios* $\{\mathbf{P}_j\}_{j \in T}$;

A.2 Dataset details

A.2.1 Stock pool details

- **SSE 50:** This index includes the 50 largest and most liquid stocks on the Shanghai Stock Exchange, mainly large state-owned enterprises and industry leaders. It is stable and blue-chip, suitable for risk-averse and long-term investors focusing on defensive strategies.
- **CSI 300:** Comprising the top 300 stocks from the Shanghai and Shenzhen markets, this index covers diverse industries and company sizes, offering broad market representation. It is ideal for investors seeking diversification and medium- to long-term returns.
- **ChiNext 100:** Featuring 100 stocks from the Shenzhen ChiNext Market, this index focuses on high-tech and innovative firms. Known for its growth potential and higher volatility, it suits investors with high-risk tolerance and those interested in technology sectors.
- **CSI A500:** This index selects 500 leading stocks from A-shares, covering all 35 CSI secondary industries and 91 out of 93 tertiary industries. It emphasizes sector-balanced exposure, ESG screening, and inclusion of innovative "New Quality Productivity" sectors (e.g., IT, industrials, healthcare). With strong profitability (71% of A-share net profits) and low valuation (14.16x P/E), it serves as a "China S&P 500" for diversified core-asset allocation and long-term growth strategies.

A.2.2 Dataset construction details

We construct our dataset with individual stock data and macroeconomic data.

Individual stock data

- **News**: Stock news is collected from various data sources. We use their titles and summaries as a substitute.
- **Financial Report**: Financial Report is collected from Wind API. We use their titles and summaries as a substitute.
- **E/P_TTM**: The inverse of the P/E ratio (E/P) indicates the earnings yield, showing the percentage of profit generated per dollar invested in the stock.
- **B/P_TTM**: Inverse of P/B (B/P) indicates the book yield, showing the return on book value per dollar invested.
- **S/P_TTM**: The inverse of the price-to-sales ratio (S/P) reflects the sales yield, quantifying the amount of sales revenue generated for each dollar invested in the company. A higher value indicates greater efficiency in converting investment into sales.
- **CF/P_TTM**: Inverse of P/CF (CF/P) shows the cash flow yield, representing cash flow generated per dollar invested.
- **Log-orthogonalized E/P**: Log-orthogonalized version of E/P, removing some kind of cap basis.Log-orthogonalized version of E/P, removing some kind of cap basis.
- **Log-orthogonalized B/P**:Log-orthogonalized version of the book-to-price ratio, which accounts for and removes certain capitalization effects, thereby isolating the information content of B/P independent of market capitalization.
- **Log-orthogonalized CF/P**:The log-orthogonalized version of the cash flow-to-price ratio, which is employed to control for capitalization influences, ensuring that the ratio captures the true predictive power of cash flow relative to price.
- **Log-orthogonalized S/P**:Log-orthogonalized version of S/P, removing some kind of cap basis.
- **EBITDA/EV**: Measures a company's return on enterprise value, indicating operating earnings (EBITDA) generated per dollar of EV.
- **ROE** : ROE measures profitability by indicating how much net income is generated for each dollar of shareholders' equity. Higher values signify more effective utilization of equity capital to generate earnings.
- **ROE stability**: TS_Mean(ROE, 8) / TS_Std(ROE, 8), measuring both absolute value and stability of ROE.
- **ROA stability**: TS_Mean(ROA, 8) / TS_Std(ROE, 8), measuring both absolute value and stability of ROA.
- **Dividend yield**: Dividend yield indicates annual dividends received per dollar invested, expressed as a percentage of the stock price.
- **Log-orthogonalized dividend yield**: Log-orthogonalized version of dividend yield, removing some kind of cap basis.
- **Dividend yield incl repo & mjrholder trans**: Dividend yield including stock repurchasing and major holder trading.
- **Revenue TTM YoY growth rate**: Measures the percentage change in trailing twelve months' revenue compared to the same period last year.
- **Net profit TTM YoY growth rate**: Measures the percentage change in trailing twelve months' net profit compared to the same period last year.
- **Non-GAAP net profit YoY growth rate**: Indicates the percentage change in non-GAAP net profit compared to the same period last year.
- **Interday volatility**: The price fluctuation range of a stock across trading days.
- **Liquidity**: Weighted average of monthly, quarterly, and yearly turnover ratios.

- **Residual volatility**: Residual volatility measures the unexplained variability in a security's returns after accounting for market or factor influences, indicating idiosyncratic risk.
- **Stock Base data**: The open, high, low, close, volume, and value data of individual stocks on a daily timeframe. (forward-adjusted)
- **industry index return**: One-day return of holding the sector's constituent stocks.
- **Price-volume feature**: Various features extracted from Alpha 158 (Yang et al., 2020) based on price and volume.

Macroeconomic data

- The latest 1-year loan prime rate.
- The latest month China CPI YOY growth rate.
- The latest yield of China ten ten-year government bonds.
- The latest PE and PE quantile of the CSI 300 index.

A.3 MORE DETAILS ABOUT MASS

A.3.1 MORE DETAILS OF MARKET DISAGREEMENT HYPOTHESIS

Market disagreement describes heterogeneous investor beliefs that drive trading activities. The market disagreement hypothesis posits that such divergence systematically distorts security valuations: when optimistic investors dominate trading while pessimists face short-selling constraints, securities become overpriced and exhibit lower future returns (Miller, 1977). This theory establishes disagreement as a persistent market friction that generates predictable return patterns, with empirical studies confirming that **high-disagreement stocks consistently underperform consensus-driven counterparts** (Diether et al., 2002; Sadka & Scherbina, 2007).

A.3.2 THE DESIGN OF INVESTOR INITIALIZATION

System & User Prompts

System Prompt
You are a helpful assistant. Make sure you carefully and fully understand the details of the user's requirements before you start solving the problem.

User Prompt
Give the following input data:
1. Input time-series data column name and their descriptions in JSON format(textual data example).
2. latest macroeconomic and market insights. Please try to analyze and summarize an abstract investing style description.
The output format is a json. The specific format of the output JSON is:
{ "Outline": "The outline and general description for investment style within 50 words. The outline is a summarization about your investing strategy and your insights into the subsequent trend of the stock market, without any details below.",
"Details": { "Risk Appetite": "conservative | moderate | moderately conservative | moderately aggressive | aggressive",
"Holding Period": "one day | about one week | about one month | about half a year | more than one year",
"Strategy Consistency": [0, 1] (Refers to the investor's ability to adhere to and execute their investment strategy with persistence and coherence, regardless of short-term market fluctuations or emotional influences. Higher number means high consistency",
"Rationality": [0, 1] (Refers to whether the investor's decision-making process is based on logic, data, and long-term objectives rather than emotions, biases, or short-term market noise. Higher number means high rationality",
"StockPoolSelector": "Specify what kind of preference you'd like to construct your watchlist stocks. The possible preferences are:
1. RandomStockSelector: Randomly construct your watchlist.
2. IndustryEqualStockSelector: Construct a stock pool with balanced distribution across industries.
3. MVEqualStockSelector: Construct a stock pool with balanced distribution across market capitalizations.

```
4.IndustryBasisStockSelector: Prefer stocks from specific industries and output the
preferred industries. The result is presented in a list format.",
"Others": "Extra information about your investing strategy, maybe correlated with
latest market and macroeconmic information and others. No more than 30 words." } }
{examples}
Input data:
E/P,B/P,CF/P, S/P,Log-orthogonalized E/P,Log-orthogonalized B/P,Log-orthogonalized
CF/P,Log-orthogonalized S/P,
Macro data:
The latest 1-year loan prime rate is 3.45. The latest month China CPI YOY growth rate
is -0.5. The latest yield of China's ten-year government bonds is 2.6733%, while the
yield has increased 0 BP over the past one day, increased -4 BP over the past one month,
and increased -21 BP over the past half a year. The latest CSI_300 PE is 10.9478,
and the current PE ratio of the CSI 300 is at the 5.4th percentile over the past 5
years(0 indicates most undervalued, and 100 indicates most overvalued). The latest
market sentiment index got a 0.63% return.
Your investing style:
{'Outline': 'A value-oriented investment approach focusing on fundamentally strong
companies with a long-term perspective, leveraging current market undervaluation and
stable economic indicators to build a diversified portfolio.',
'Details': {'Risk Appetite': 'moderate', 'Holding Period': 'more than one
year', 'Strategy Consistency': '0.85', 'Rationality': '0.9', 'StockPoolSelector':
'IndustryEqualStockSelector', 'Others': 'Leverage low CPI and undervalued CSI 300
PE for potential upside.'}
(END_OF_EXAMPLES)
Input data: {input_data}
Macro data: {macro_data}
Your investing style:
```

A.3.3 THE DESIGN OF INVESTMENT STRATEGY EXECUTION

User Prompts

User Prompt

```
Giving following
1. Input data in table format and their descriptions in JSON format.
2. investing style to make investment decisions in JSON format.
Please output {num_stocks} stocks you tend to invest in. The result is in JSON format,
key is "Stock", and value is a list containing the stock code. Please make sure:
1. You output legal stock code. The stock code is legal if and only if it is in the
input data "Stock" list.
2. The number of stock codes is correct, actually equal to {num_stocks}. Here is an
example.
For stock_nums in investing instructions, we use 3 in this example. Input Data for
investing decision:
```

1. **Input Data Description**:

```
{"E/P": "The inverse of the P/E ratio (E/P) indicates the earnings yield, showing the
percentage of profit generated per dollar invested in the stock.",
"B/P": "Inverse of P/B (B/P) indicates the book yield, showing the return on book value
per dollar invested.",
"S/P": "Inverse of P/S (S/P) reflects the sales yield, showing sales generated per
dollar invested.",
"CF/P": "Inverse of P/CF (CF/P) shows the cash flow yield, representing cash flow
generated per dollar invested.",
"Log-orthogonalized E/P": "Log-orthogonalized version of E/P, removing some kind of
cap basis.",
"Log-orthogonalized B/P": "Log-orthogonalized version of B/P, removing some kind of
cap basis.",
"Log-orthogonalized CF/P": "Log-orthogonalized version of CF/P, removing some kind of
cap basis.",
"Log-orthogonalized S/P": "Log-orthogonalized version of S/P, removing some kind of
cap basis.",
```

```
"EBITDA/EV": "Measures a company's return on enterprise value, indicating operating
earnings (EBITDA) generated per dollar of EV."}
2. Investing Style:
{"Outline": "A value-driven investment approach focusing on stocks with strong
fundamentals, undervalued valuations, and consistent cash flows over the long term.",
"Details": { "Risk Appetite": "Moderately conservative", "Holding Period": "More than
one year", "Strategy Consistency": "0.85", "Rationality": "0.9", "StockPoolSelector":
"MVEqualStockSelector" }}
3. Input data:
',Stock,Date,E/P,B/P,CF/P,S/P,
Log-orthogonalized E/P,Log-orthogonalized B/P,Log-orthogonalized CF/P,
Log-orthogonalized S/P, EBITDA/EV,
965494,000858,20190102, 0.06295366,
0.30744636,0.038947526,0.19324197,
-4.032941,-1.1295723,3.594055,
-1.2754831,0.124886042941460,
002594,20190102,0.020888906,
0.37708813,0.09185906,0.9017491,-4.038043,
-0.6966869,5.084233,0.3152281,0.09258402716,
600519,20190102,0.042301364,0.13605072,
0.036664255,0.09038502,-7.6968794,-2.2439895,
1.2049837,-2.2207088,0.0797575348104294,
600900,20190102,0.066111766,0.4052357,0.1183,
0.15322393,-5.3881683,-1.0025798,3.743841,
-1.5840118,0.1050353948267292,601012,
20190102,0.062190603,0.30756927,0.032795224,
0.41643697,-0.72993636,-0.7708632,
5.801872,-0.31826368,0.0887390158431868,
601288,20190102,0.16604953,1.2584949,
0.12149128,0.4757528,-7.5973797,-0.1158539,
1.556502,-0.6272717,0.059454748665067,
601888,20190102,0.02850359,0.1358013,
0.034710173,0.35662726,-3.433404,-1.7193639,
4.34933,-0.59344673,0.0511954139068489,
603259,20190102,0.024971908,0.12955885,
0.018961666,0.10751114,-2.9358995,
-1.8100101,4.314365,-1.7471998,0.04303389'
LLM output:
{'Stock': ['000858', '600900', '601288']}
Note that in this example, we ask LLM to output 3 stocks. However, in real scenarios,
you should follow the "num_stocks" args in the instruction.
(END OF EXAMPLES)
{input_data}
```

A.3.4 Time complexity and token cost

Table 3: MASS 's average time cost and api call fees on each trading day.

Stock Pool	Time	Cost
SSE50	125s	\$0.679
CSI 300	378s	\$2.265
Chi Next 100	227s	\$1.192

For practical deployment, the operational efficiency of MASS is a key consideration. We have incorporated several strategic design choices to minimize API-related costs and ensure computational feasibility in a live trading scenario.

First, we recognize that the macroeconomic data informing the investor initialization module (Section 3.1.1) changes at a low frequency. For instance, metrics like the CPI growth rate are updated monthly, while others, such as government bond yields and market-wide PE percentiles, evolve gradually. To substantially mitigate API overhead, we therefore limit the re-invocation of this initialization module to only once per week, specifically on the first trading day.

Second, and critically, we cache the individual investment decisions generated by each agent during the forward propagation stage. Consequently, the backward optimization process—while computationally intensive in its re-aggregation of historical signals for different candidate distributions—operates entirely on these cached results. This design ensures that the backward optimization step incurs **zero additional LLM token costs**.

These optimization strategies ensure the economic viability of MASS in a real-world setting. To provide a transparent assessment of its practicality, we report the average daily computational time and API costs for a 512-agent configuration in Table 3.

A.4 BASELINE DETAILS

- **Proxy indicators**: Various features can be used as a proxy to quantify market disagreement (Diether et al., 2002). We use the earning stability of the listed company (implemented by calculating the std of annualized ROE) as a baseline.
- **LightGBM**: A high-efficiency, leaf-wise gradient boosting decision tree framework by Microsoft Research, employing histogram-based algorithms for accelerated training and reduced memory footprint. Following (Bali et al., 2023) and Equation 4, we simulate market disagreement by constructing various LightGBM agents visible to different features.
- **DTML**: DTML (Yoo et al., 2021) is an attention-based model that exploits the correlations between stocks to make investment decisions. We use the open-source implementation [3] to implement this baseline.
- **MASTER**: MASTER (Li et al., 2024b) is a stock transformer for stock price forecasting, which models the momentary and cross-time stock correlation and guides feature selection with market information. We use the open-source implementation [4] to implement this baseline.
- **SEP**: SEP (Koa et al., 2024) utilizes a verbal self-reflective agent and A PPO that allows the LLM to teach itself how to generate explainable single stock predictions. We use the open-source link [5] to implement SEP.
- **FINCON**: FINCON (Yu et al., 2024) is a multi-agent framework for single stock price prediction and simple investment portfolio construction with conceptual verbal reinforcement.
- **TradingAgents**: TradingAgents (Xiao et al., 2025b) is a multi-agent framework. that utilizes trading firms' collaborative dynamics to construct investment portfolios. We use the open-source link [6] to implement TradingAgents.

A.5 FURTHER EXPERIMENT RESULTS ON MORE EVALUATION METRICS

In this section, we provide more evaluation metrics to demonstrate the superiority of MASS. These metrics are as follows:

1. **Annualized Return (AR)**
   The average annual return of the strategy, calculated by scaling the periodic return (e.g., daily, monthly) to an annual basis. It reflects the strategy's profitability over time, with the formula:
   $$R_{\text{annual}} = (1 + R_{\text{periodic}})^n - 1$$
   where n is the number of periods in a year.
2. **Maximum Drawdown (MDD)**
   The largest peak-to-trough decline in portfolio value, expressed as a percentage. It measures the strategy's downside risk, defined as:
   $$\text{MDD} = \max\left(1 - \frac{V_t}{V_{\text{peak}}}\right)$$
   where V_t is the portfolio value at time t, and V_{peak} is the maximum value before t.

[3] `https://github.com/ceteris11/DTML`
[4] `https://github.com/SJTU-DMTai/MASTER`
[5] `https://github.com/koa-fin/sep`
[6] `https://github.com/TauricResearch/TradingAgents`

Table 4: Comparisons with baselines on more evaluation metrics. MASS outperforms all others across all 3 stock pools, showing impressive cumulative returns compared to the stock index. The best performance in each column is highlighted in **bold**.

Main Experiments (Throughout 2023)									
Method	**SSE50**			**CSI 300**			**Chi Next 100**		
	AR	Sharpe	MDD	AR	Sharpe	MDD	AR	Sharpe	MDD
Proxy Indicator (Diether et al., 2002)	-2.39	-1.22	14.04	-3.60	-1.62	20.57	-20.01	-3.24	24.15
LightGBM (Ke et al., 2017)	-1.88	-1.14	13.16	-4.55	-2.12	18.57	-19.32	-3.01	23.96
DTML (Yoo et al., 2021)	-1.69	-1.08	12.99	-0.33	-0.14	22.34	-8.23	-3.20	24.55
MASTER (Li et al., 2024b)	-1.67	-0.92	12.91	0.79	0.33	22.05	-7.88	-3.17	24.06
SEP (Koa et al., 2024)	-2.01	-1.07	13.12	-10.24	-4.32	22.67	-6.84	-3.14	24.01
FinCON (Yu et al., 2024)	-1.82	-0.98	13.05	-9.25	-3.28	23.74	-6.01	-2.80	23.75
TradingAgents (Xiao et al., 2025b)	-2.44	-1.71	13.15	-7.19	-3.02	19.61	-4.65	-2.82	23.84
MASS	**2.16**	**1.98**	**11.98**	**4.95**	**2.23**	**14.04**	**1.17**	**0.99**	**19.06**
Stock pool Index	-9.98	-2.37	21.62	-9.75	-2.92	21.44	-19.18	-3.17	32.26

Experiments on data leakage concern (The first quarter of 2025)									
Method	**SSE50**			**CSI 300**			**CSI A500**		
	AR	Sharpe	MDD	AR	Sharpe	MDD	AR	Sharpe	MDD
MASS	**9.74**	**2.42**	**2.91**	**9.36**	**2.66**	**2.99**	**11.34**	**2.93**	**4.08**
Stock pool Index	-1.88	-2.97	5.63	-3.88	-3.15	5.86	-1.28	-3.26	6.04

3. **Sharpe Ratio (Sharpe)**
   A measure of risk-adjusted return, calculated as the excess return over the risk-free rate divided by the strategy's volatility:

$$\text{SR} = \frac{R_{\text{strategy}} - R_f}{\sigma_{\text{strategy}}}$$

   where R_f is the risk-free rate and σ_{strategy} denotes the standard deviation of strategy returns. A higher value indicates superior risk-adjusted performance.

A.6 BACKTESTING EXPERIMENTS DETAILS

We conduct backtesting experiments on a simulated system. We conduct backtesting using a traditional index-enhancement strategy. The portfolio is rebalanced weekly, with a round-trip transaction cost of 0.1%. During the first fifteen minutes after the market opens on the first trading day of each week, we first exclude stocks that are limit-up or limit-down. Subsequently, we rank the portfolio construction signals and equally weight the top 20% of the ranked stocks. Stocks currently held but no longer in the top 20% are sold.