- **Volatility (Vol)**: The standard deviation of the return vector $\mathbf{r}$, measuring the uncertainty of the return rate. It is calculated as:

$$Vol = \sqrt{252} \times \sigma[\mathbf{r}]$$

- **Maximum Drawdown (MDD)**: The largest single drop from peak to trough before a new peak is achieved. It is defined as:

$$MDD = \max_{0 \leq \tau \leq T} \left[\max_{0 \leq t \leq \tau} \left(\frac{n_t - n_\tau}{n_t} \right) \right]$$

Diversity Metrics:

- **Entropy (ENT)**: A measure of the diversity of bets taken by a strategy, calculated using the Shannon entropy formula. It is given by:

$$ENT = -\sum_{i=1}^{N} p_i \log(p_i)$$

- **Effect Number of Bets (ENB)**: A measure of the effective number of bets that contribute to the portfolio's performance. It is calculated as:

$$ENB = \frac{1}{\sum_{i=1}^{N} (p_i \log(p_i))^2}$$

I Details of Baselines

To comprehensively evaluate the performance of QuantAgents in investment decision-making, we selected a variety of classical and cutting-edge baseline models for comparison. These include three classical rule-based quantitative investment strategies (Classical methods): MV, ZMR, and TSM; three reinforcement learning-based financial agents (RL-based methods): SAC, DeepTrader, and AlphaMix+; and three investment methods based on LLM models (LLM-based methods): FinGPT, FinMem, and FinAgent. A brief introduction to each method is provided below:

- **Classical Methods**

– **Mean-Variance (MV)** is a traditional portfolio optimization strategy that seeks to maximize returns for a given level of risk, or equivalently, minimize risk for a given level of expected returns.

– **Z-score Mean Reversion (ZMR)** assumes that asset prices will revert to their mean over time, using Z-scores to measure the deviation from the mean and identify overbought or oversold conditions.

– **Time Series Momentum (TSM)** is a strategy that exploits momentum in financial markets by investing in assets that have performed well in the past and shorting those that have not.

- **RL-based Methods**

– **Soft Actor-Critic (SAC)** is a state-of-the-art off-policy reinforcement learning algorithm that uses entropy regularization to balance exploration and exploitation in trading strategies.

– **DeepTrader** is a deep reinforcement learning method that optimizes investment policy by embedding macro market conditions to dynamically adjust the proportion between long and short funds, aiming to lower the risk of market fluctuations.

– **AlphaMix+** leverages mixture-of-experts and risk-sensitive approaches to make diversified risk-aware investment decisions, focusing on a comprehensive evaluation framework that includes profitability, risk-control, and other critical axes.

- **LLM-based Methods**

– **FinGPT** is an open-source LLM framework that processes textual and numerical inputs to generate insightful financial decisions, offering advantages over traditional strategies.

– **FinMem** is an advanced LLM agent framework for automated trading, optimized through fine-tuning to enhance performance and returns.

– **FinAgent** is a multimodal foundational agent designed for financial trading tasks, incorporating market intelligence and a dual-level reflection module to adapt to market dynamics and improve decision-making processes.

– **HedgeAgents** is a multi-agent financial trading system leveraging LLMs for robust hedging strategies, featuring specialized analysts and a manager coordinating via conferences to optimize returns and risk management.

J Experiment of Ablation Study

J.1 Effectiveness of Each Conference

Cumulative returns of ablation analysis on three conference, as shown in Figure 8 .

Table 5: Performance comparison of different LLM as the backbone for QuantAgents on 9 evaluation metrics.

LLM	ARR(%)	TR(%)	SR	CR	SoR	MDD(%)	VoL(%)	ENT	ENB
ChatGLM3-6B	37.32	158.99	2.14	6.89	45.98	28.56	1.62	2.41	1.22
Llama-2-13b-chat	40.38	176.66	2.35	8.08	50.77	24.15	<u>1.51</u>	2.53	1.26
Qwen2-72B-Instruct	44.13	199.41	2.23	8.59	49.22	24.52	1.77	2.66	1.33
GPT-4-1106-preview	53.77	263.63	<u>2.71</u>	8.76	<u>60.11</u>	23.79	1.61	2.79	1.38
Claude 3.5 Sonnet	<u>57.95</u>	<u>294.07</u>	2.67	<u>10.87</u>	53.74	<u>22.33</u>	1.76	<u>2.86</u>	<u>1.47</u>
GPT-4o-2024-05-13	**58.68**	**299.55**	**3.11**	**11.38**	**66.94**	**16.86**	**1.43**	**2.97**	**1.49**

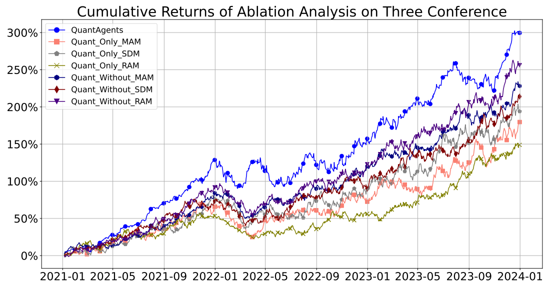

Figure 8: Cumulative Returns of Ablation Analysis on Three Conference

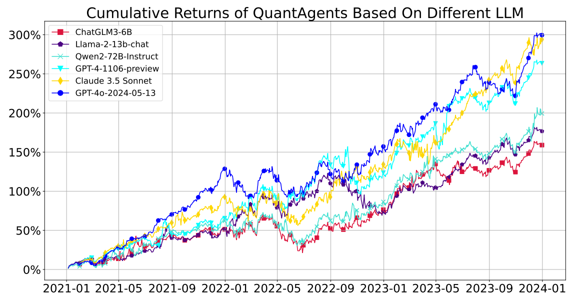

Figure 9: Cumulative Returns of QuantAgents Based on Different LLM

J.2 Effectiveness of LLM Backbone

For using different LLM as the backbone for QuantAgents, their experimental results are presented in Table 5, and the cumulative returns chart is in Figure 9.

K Single-Asset Performance Comparison

To evaluate the effectiveness of all models in a single-asset scenario, we conducted experiments on Apple Inc. (AAPL) stock from 2021-01-01 to 2023-12-31. Figure 10 illustrates the performance comparison between QuantAgents and baseline models.

The results demonstrate a clear performance hierarchy: 1) RL-based methods outperform rule-based strategies in managing AAPL stock. For instance, SAC achieved a cumulative return

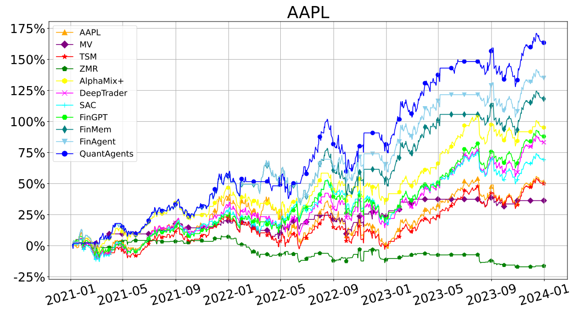

Figure 10: Performance comparison of QuantAgents and baseline models on AAPL stock from January 2021 to December 2023.

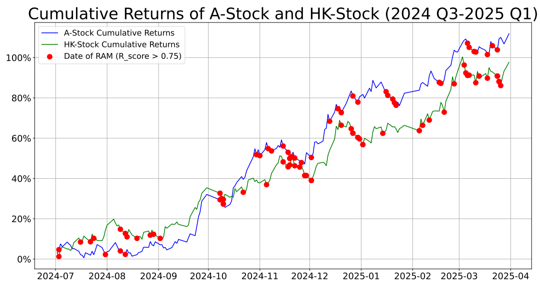

Figure 11: Cumulative Returns of QuantAgents during live trading (24Q3-25Q1). RAM were held 36 times in the A-stock and 46 times in the HK stock market.

of 69.20% compared to TSM's 49.92%. This superiority stems from RL methods' ability to adapt to AAPL's high volatility and learn from historical price patterns, enabling more dynamic trading strategies. 2) LLM-based methods surpass RL-based approaches in AAPL trading. For example, FinAgent reached a 135.02% cumulative return, compared to DeepTrader's 83.22%. This improvement is attributed to LLMs' capacity to process and interpret AAPL-specific news, earnings reports, and market sentiments, allowing for more informed decision-making in response to company events and sector trends. 3) QuantAgents exhibits superior performance with a 163.38% cumulative return on AAPL, significantly outperforming all baselines. This exceptional performance stems from its multi-agent architecture, which allows for specialized analysis of AAPL's price movements, market sentiment, and sector trends.

The integration of advanced LLMs enables QuantAgents to process AAPL-related news and financial reports more effectively. Additionally, the dual reward mechanism enhances QuantAgents' ability to balance risk and return specifically for AAPL stock, resulting in more stable performance during both bullish and bearish periods in the stock.

L Empirical Evaluation of QuantAgents in Live Trading

Table 6: Performance Metrics of QuantAgents in Live Trading (Q3 2024–Q1 2025).

Market	Total Return (%)	Sharpe Ratio	Win Rate (%)
A-stocks	111.87	2.02	61.23
HK-stocks	97.69	1.76	59.71

To rigorously validate the efficacy of QuantAgents, we conducted an extensive evaluation of its live trading performance in the A-stock (Shanghai and Shenzhen) and HK-stock (Hong Kong) markets over the period from Q3 2024 to Q1 2025. These markets were selected due to their distinct characteristics: A-stocks exhibit high volatility and liquidity driven by domestic retail investors, while HK-stocks are influenced by international capital flows and stricter regulatory frameworks. This diversity tests QuantAgents' adaptability to varying market dynamics.

The experimental setup involved deploying QuantAgents in a live trading environment with a diversified portfolio, adhering to real-world constraints such as transaction costs and market impact. Risk Alert Meetings (RAM) were convened to monitor and mitigate potential downturns, occurring 36 times for A-stocks and 46 times for HK-stocks, reflecting the latter's higher volatility. Figure 11 illustrates the cumulative returns over the evaluation period.

QuantAgents achieved superior returns of 111.87% in the A-stock market, with a Sharpe Ratio of 2.02 and a Win Rate of 61.23%, demonstrating robust profitability under volatile conditions. In the HK-stock market, it recorded returns of 97.69%, with a Sharpe Ratio of 1.76 and a Win Rate of 59.71%, showcasing consistent performance despite international market complexities. These results, detailed in Table 6, highlight QuantAgents' exceptional profitability and risk management capabilities across diverse market conditions, underscoring its potential for real-world financial applications.

M Conclusions of Appendix

In this nearly 15 page appendix, we provide additional details about our framework (Section Definitions of Single Agent, Prompt Templates for Various Tasks,Profiles of Agents), experimental settings (Section PRUDEX Evaluation Benchmark, Details of Dataset Setup, Details of Evaluation Metrics, Details of Baselines, Construction of the Strategy Pool), and a more additional experiments (Section Experiment of Ablation Study, Single-Asset Performance Comparison,Empirical Evaluation of QuantAgents in Live Trading). We hope that our efforts will serve as a source of inspiration for more readers!