Table 3: Overview of LLM-based Trading Agents and Their Architectures

Method	Backbone	Agents / Modules	Position-Aware	Information Processed	Decision Structure
FinPOS	GPT-4o	10 agents: 4 filters + 4 analyzers + Direction Agent + Quantity/Risk Agent	Yes (continuous position state + CVaR sizing)	Price, news, macro events, 10-K/10-Q reports	Two-stage: (1) direction reasoning; (2) CVaR-based position sizing; reflection with multi-timescale reward
FinCon	GPT-4o	7 agents: Data, News, Report, Analyst Report, Earnings Call, Stock Selection, Manager	No (no explicit position sizing; only discrete actions)	Structured & unstructured financial data	Multistage pipeline with manager aggregation; buy/sell/hold
FinAgent	GPT-4o	10+ agents: Fundamental Analyst, Sentiment Analyst, News Analyst, Technical Analyst, Bullish/Bearish Researchers, Trader, Risk (3 agents), Fund Manager	No (no explicit position sizing; only discrete actions)	Sentiment, technical indicators, news, fundamentals (e.g., revenue, profit, debt)	Debate + risk-check pipeline; buy/sell/hold
FinGPT	llama (fine-tuned)	Single agent	No	Sentiment signals + price	Generates buy/sell signals with fixed trade size
FinMem	GPT-4o	Single agent	No (memory guides reasoning only)	Data, News, 10-K/10-Q	Single-step; buy/sell/hold

Table 4: Key Hyperparameters for RL Agents

Agent	Key Hyperparameters	Value
A2C	n_steps	5
	ent_coef	0.01
	learning_rate	0.0007
PPO	n_steps	2048
	ent_coef	0.01
	learning_rate	0.00025
	batch_size	64
DQN	batch_size	128
	buffer_size	50000
	learning_rate	0.001

Table 5: Sensitivity Analysis of FinPOS under Different LLM Sampling Hyperparameters (TSLA)

Sampling Setting	CR (%)	SR	MDD (%)
Default (T=0.7, p=0.9)	62.15	0.68	42.34
T=0.7, p=0.85	61.74	0.67	42.50
T=0.7, p=0.80	62.01	0.66	42.40
T=0.8, p=0.9	60.13	0.66	45.05
T=0.5, p=0.9	61.07	0.64	43.10

awareness consistently improves risk-adjusted performance across different stocks.

D.3 More Details of Ablation Studies

D.3.1 Financial Insight Prompting (FIP)

Financial Insight Prompting (FIP): A targeted prompting strategy designed to mitigate LLMs' weaknesses in financial reasoning. It gradually instills financial thinking by emphasizing causal chains, market trend, and probabilistic inference.

Introducing FIP leads to a clear overall performance gain, consistently enhancing cumulative return across all assets (e.g., TSLA: 52.56% → 62.15%; AAPL: 59.38% → 67.31%). To investigate the impact of prompt design on the depth of agent finance insight, we divide the content of prompts into eight key dimensions: Role Setting, Task Breakdown, Depth Analysis, Multi-Dimensional Analysis, Logical Reasoning, Contextual Consideration, Actionability, and Clarity & Conciseness(the detailed explanations of these eight dimensions are provided in Tab. 6). For each dimension, we design prompts with different levels of refinement—Low, Medium, and High—and conduct graded experiments. The results are shown in Fig. 5.

The results indicate that Task Breakdown, Depth Analysis, and Multi-dimensional Analysis are the most influential dimensions for overall agent performance. Notably, Depth Analysis plays a particularly crucial role in financial reasoning: since the quality of financial analysis is significantly influenced by deep insights, particularly those concerning causal chains and risk-reward tradeoffs. In contrast, Multi-Dimensional Analysis presents a more nuanced pattern. Financial analysis naturally spans across multiple perspectives, such as macro vs. micro and short-term vs. long-term. While moderate prompting enhances the model's ability to cover multiple factors, overly elaborate prompts may overwhelm the LLM, causing it to "overthink," lose focus, and eventually degrade performance—an effect we refer to as the informa-
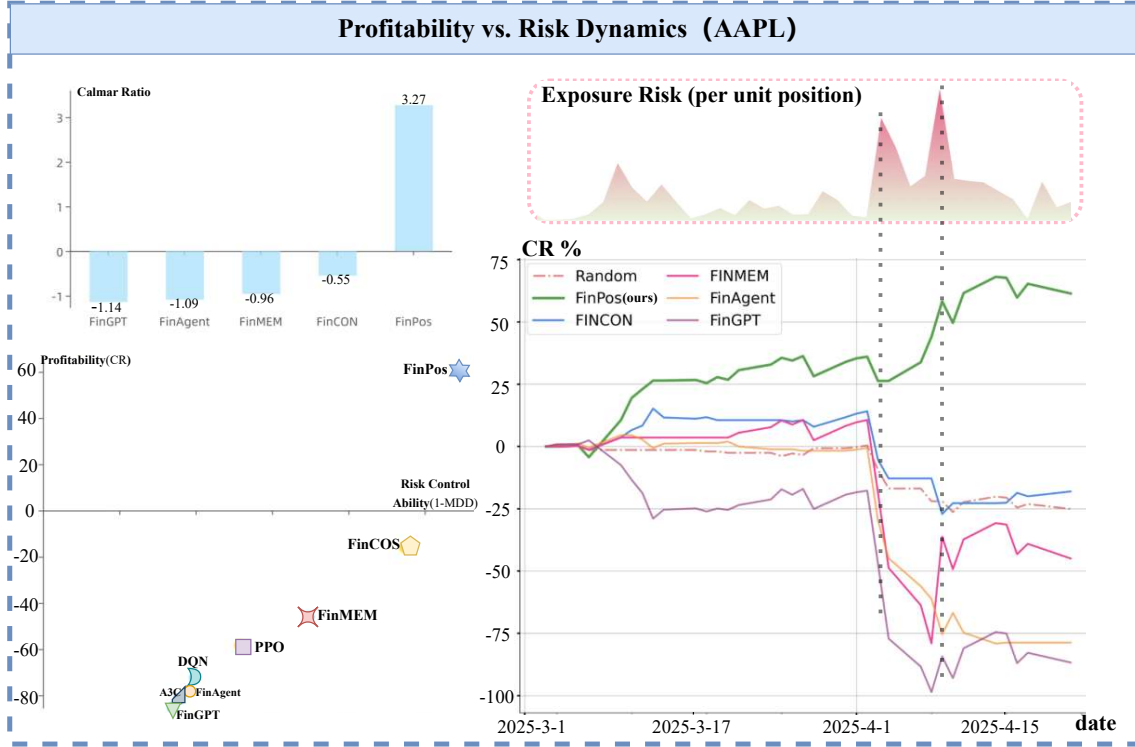
Figure 6: Profitability versus risk dynamics. Top-left: Calmar ratio, capturing return relative to maximum drawdown (higher is better). Bottom-left: joint view of profitability (CR%) and risk-control (1 - MDD), indicating return-risk balance. Right: time-series comparison of cumulative return (bottom) and exposure risk (top) across major events; PA-aware strategies mitigate exposure spikes and sustain more stable growth.

tion burden. Among the eight dimensions, Contextual Consideration shows the most pronounced performance shift. Without explicit prompting, the model tends to overlook this dimension—for instance, it may treat tariff adjustments as entirely unrelated to stock prices. Once guided, however, the agent develops stronger contextual reasoning: it can link major events (e.g., political shifts, regulatory changes) to firm-level responses (e.g., strategic adjustments to tariffs), and further to market outcomes. This ability allows the model to generate insights that align more closely with real-world market dynamics.

Overall, the optimal strategy in FIP design is to selectively emphasize key dimensions—particularly Depth Analysis, Contextual Consideration, and Logical Reasoning—while keeping the prompt concise and focused. Such design not only improves the quality of reasoning but also ensures that the conclusions provide actionable guidance in real financial markets.

D.3.2 Signal Ablation across Analyst Agents

To better isolate the contributions of individual information sources, we conduct an agent-wise signal ablation study by selectively disabling specific analyst agents while keeping all other components unchanged. This design allows us to quantify the marginal effect of each signal type under identical market conditions.

As this experiment aims to analyze the relative importance of different information sources rather than cross-asset generalization, we report representative results on TSLA, which offers the richest and most comprehensive set of textual signals. We observe consistent qualitative trends across other assets.

As shown in Table 7, removing any individual signal source leads to a noticeable degradation in performance, though the magnitude varies by signal type. Disabling quarterly filings (10-Q) results in a relatively moderate decline. In contrast, removing annual filings (10-K) substantially increases maximum drawdown, indicating their importance in anchoring long-term risk perception. Overall, company-level news has the most pronounced im-

Table 6: Evaluation Criteria for Prompt Traits

Trait	Evaluation Criteria (How to measure)
Role Setting	Does it clearly assign a professional role to the AI (e.g., "Financial Analyst")?
Task Breakdown	Does it break down complex analytical tasks into clear sub-tasks?
Depth Requirement	Does it explicitly ask the model to infer and analyze, not just summarize or restate?
Multi-dimensional Analysis	Does it guide the model to consider multiple factors (e.g., short-term/long-term, macro/micro)?
Logical Reasoning	Does it encourage the model to build causal chains, weigh pros and cons, and infer potential impacts?
Contextual Consideration	Does it guide the model to consider non-financial factors (e.g., investor psychology, market narrative)?
Actionability	Does it require the model to provide conclusions that have practical guidance for decision-making?
Clarity & Conciseness	Is the prompt itself easy to understand, unambiguous, and not redundant?

pact on both return and risk metrics, followed by macroeconomic signals.

D.3.3 Macroeconomic News (MN) module

Beyond the experiments mentioned in the main text, FinPOS further broadens its information scope by incorporating macroeconomic news (MN) and other sources into the Market Signal Processing and Analysis module, and conducts corresponding ablation studies. The following provides examples of the decision-making process of the directional agent before and after integrating the macroeconomic news module.

- **Before incorporating MN:** I begin by reviewing latest earnings report and recent company news of TSLA. The quarterly results exceed market expectations, and Musk's announcement about expanding factory investment conveys a strong growth signal. Market sentiment around the company appears to be positive, and technical indicators show sustained upward momentum. Based on the alignment of these signals, I infer that TSLA's short-term trend is likely to be bullish. Decision: **buy**.

- **After incorporating MN:** Recent news indicates that Trump has introduced new tariffs, inflation is accelerating, and export conditions for U.S. manufacturers are deteriorating. Although TSLA's fundamentals remain strong, these macro developments imply higher production costs and potential demand pressure. After integrating these broader signals, I reassess the outlook: systemic risk outweighs company-level optimism. Decision: **sell**.

This comparison demonstrates that MN provides crucial contextual signals for decision-making, especially during periods of high market volatility or systemic risk, significantly enhancing the agent's risk awareness and decision accuracy.

D.4 FinPOS Performance under Extreme Market Conditions

To evaluate the robustness of FinPOS under highly volatile market regimes, we conduct an additional stress test over the period from March to April 2025, during which market conditions exhibit pronounced instability. This interval coincides with a series of major macroeconomic and political events, including the U.S. presidential election and heightened geopolitical tensions, leading to frequent regime shifts and elevated tail risks.

Table 8 reports the performance of different methods during this period. DRL-based approaches suffer substantial drawdowns and consistently negative risk-adjusted returns, indicating limited robustness to abrupt distributional shifts. Similarly, most LLM-based agents operating under discrete buy/sell/hold decision frameworks display unstable behavior, particularly during rapid price reversals and high-volatility episodes. In contrast, FinPOS maintains strong and consistent performance across all evaluated stocks, achieving

Table 7: Agent-wise Signal Ablation on TSLA

Enabled Signals				Performance		
Market	Company	10-Q	10-K	CR%	SR	MDD%
✓	✓	✓	✓	**62.15**	**0.68**	**42.34**
×	✓	✓	✓	51.32	0.53	55.40
✓	×	✓	✓	48.15	0.48	60.52
✓	✓	×	✓	58.59	0.63	45.11
✓	✓	✓	×	53.78	0.56	67.25