TwinMarket: A Scalable Behavioral and Social Simulation for Financial Markets

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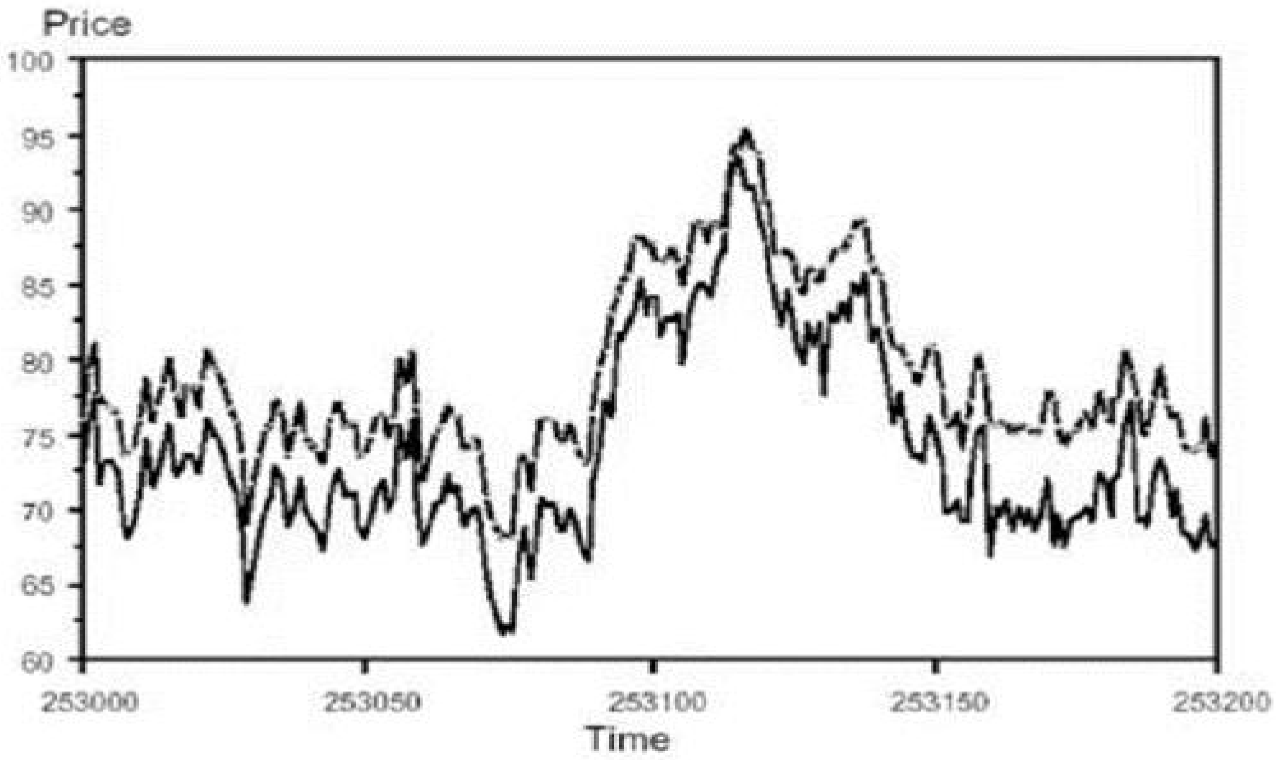
Project Page: https://freedomintelligence.github.io/TwinMarket/

Motivation

- Realistically simulate complex human behaviors
- Individuals aggregate into social systems for behavioral research



Santa Fe Institute Artificial Stock Market[1]

[1] Palmer, Richard G., et al. "Artificial economic life: a simple model of a stockmarket." *Physica D: Nonlinear Phenomena* 75.1-3 (1994): 264-274.

Limitations of Traditional ABMs

1. Oversimplify human behavior

2. Struggle to capture complexity & irrationality

3. Hard to trace causality

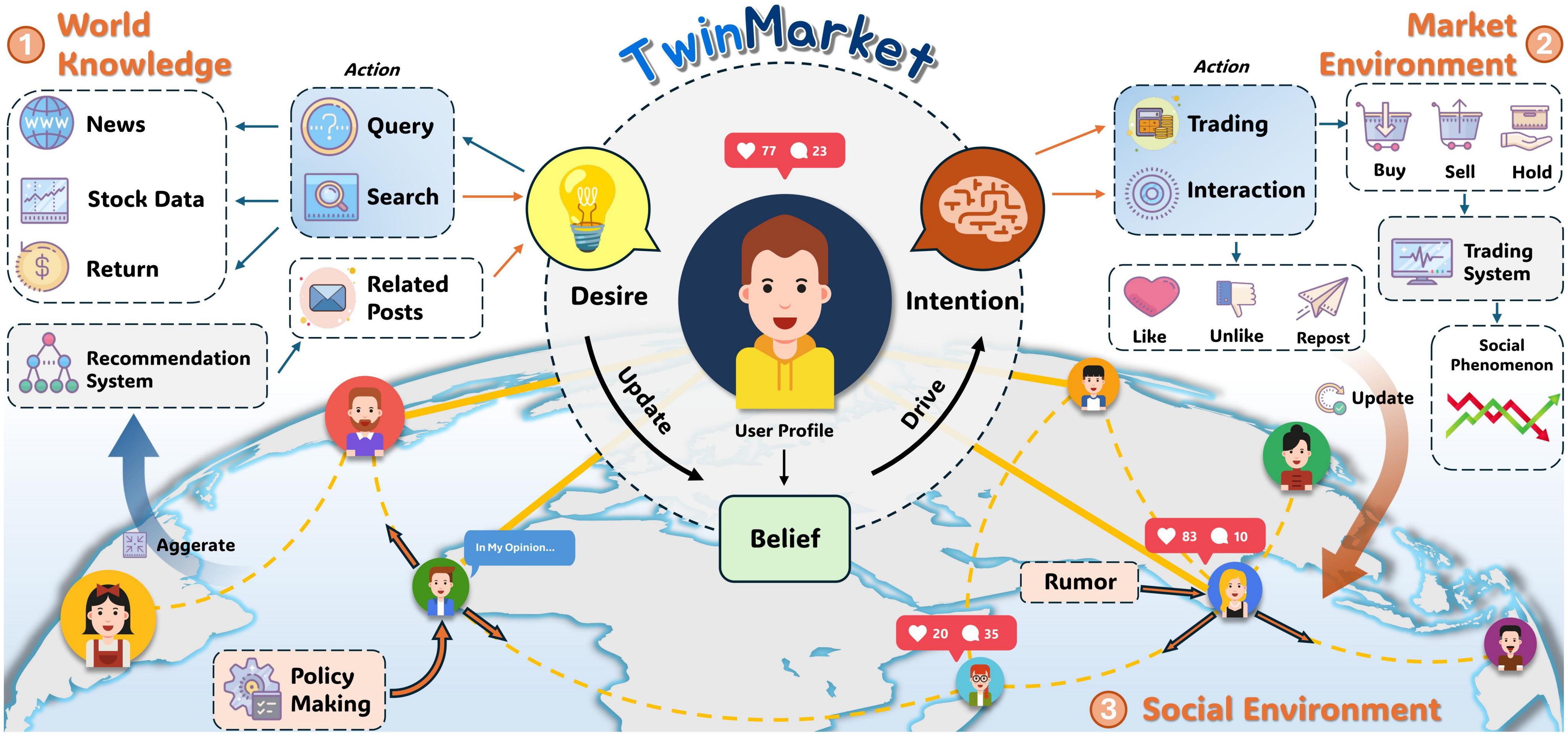
LLMs as Simulators?

- **Benefits of LLM as Simulator[2,3]** : rich behaviors, nuanced interactions, reasoning ability
- **Limitations of LLM-simulated Agent[4,5,6]** : Fixed Prompts, no interactions, limited scale

System	Agent Customization	Social Interactions	Simulation Scale
CompeteAI	Simple predefined prompts	Competition between 2 restaurants	Less than 100 agents
EconAgent	Uses demographic info	No interaction considered	100 agents
ASFM	Two fixed strategies	No interaction considered	Not disclosed
TwinMarket	Highly customizable agents	Rich multi-agent interactions	1000 agents, scalable

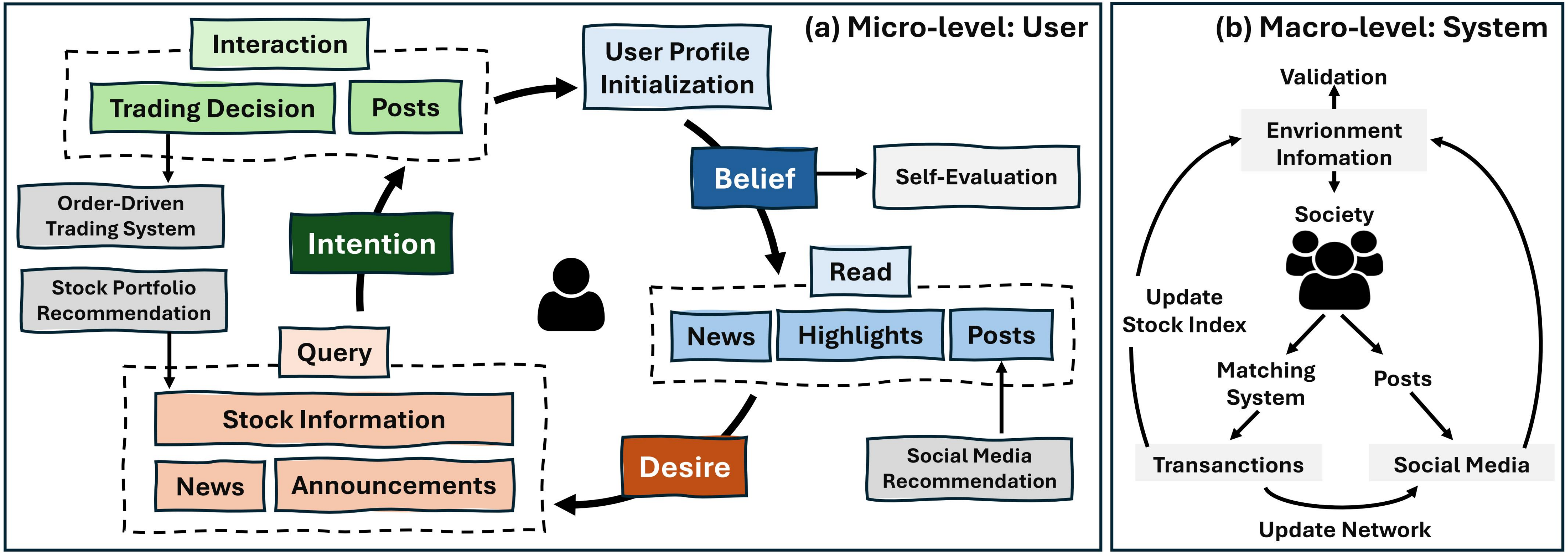
[2] Yu, Yangyang, et al. "Fincon: A synthesized llm multi-agent system with conceptual verbal reinforcement for enhanced financial decision making." Advances in Neural Information Processing Systems 37 (2024): 137010-137045.
[3] Eisfeldt, Andrea L., and Gregor Schubert. AI and Finance. No. w33076. National Bureau of Economic Research, 2024.
[4] Zhao, Qinlin, et al. "Competeai: Understanding the competition dynamics in large language model-based agents." arXiv preprint arXiv:2310.17512 (2023).
[5] Li, Nian, et al. "Econagent: large language model-empowered agents for simulating macroeconomic activities." arXiv preprint arXiv:2310.10436 (2023).
[6] Gao, Shen, et al. "Simulating financial market via large language model based agents." arXiv preprint arXiv:2406.19966 (2024).

TwinMarket Framework



TwinMarket: A loop of agents, environments, interactions, and emergence

TwinMarket Simulation Workflow



The simulation workflow driven by the Belief-Desire-Intention framework. The **micro-level** simulation focuses on modeling individual user behavior, while the **macro-level** simulation addresses the dynamics of the social media platform and trading system.

Micro-Level Simulation: BDI-Framework

The agent' state and actions are governed by three core components:

- **Belief : The agent's dynamic perception of the environment, defined as $B_t = f(S_t, H_t, N_t)$**
  - $S_t \in \mathbb{R}^5$: A belief vector encoding five dimensions (economic fundamentals, market valuation, short-term trends, market sentiment, self-assessment).
  - H_t : Historical trading records and market data.
  - N_t : Current news and social media information.
- **Desire : The agent's goal generation process, defined as $D_t = g(B_t, Q_t)$**
  - B_t : The agent's current belief state.
  - Q_t : Information retrieval queries.
- **Intention : The agent's committed action selection, defined as $I_t = h(B_t, D_t, C_t) \in \mathcal{A}$**
  - D_t : The current goal set derived from beliefs (e.g., analyze specific industries).
  - C_t : Current constraints (e.g., capital, position limits, preferences).
  - $\mathcal{A}$: The set of all possible actions, including trading actions {buy, sell, hold} and social actions {like, unlike, repost}.

Micro-Level Simulation: BDI-Framework

Daily Simulation Loop: For the daily simulation loop, the agent's state transition is defined as $Agent_{t+1} = BDI(Agent_t, Environment_t)$.

This BDI cycle follows a sequential, six-step execution order:

① **Belief Formation : $B_t = f(S_t, H_t, N_t)$ --- The agent perceives the environment.**

② **Desire Generation** : $D_t = g(B_t, Q_t)$ **--- The agent forms goals based on its beliefs.**

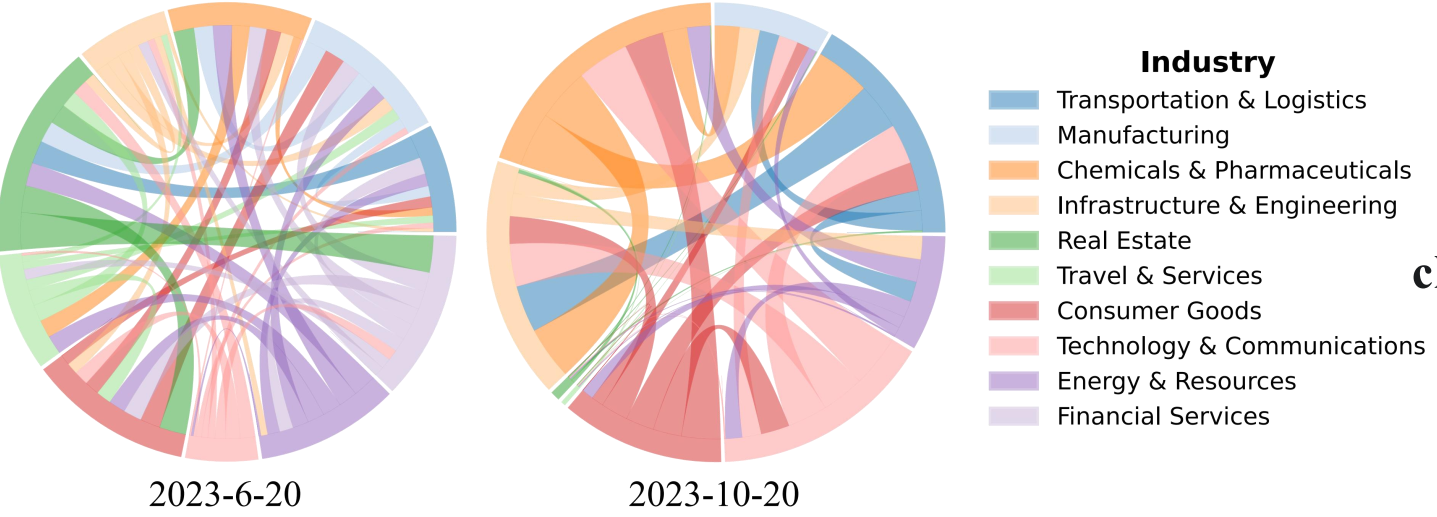
③ **Intention Planning : $I_t = h(B_t, D_t, C_t)$ --- The agent commits to specific actions.**

④ **Action Execution** : $Action_t = execute(I_t)$ **---** The agent performs the action.

⑤ **Environment Response** : $Feedback_t = Environment(Action_t)$ --- The environment provides feedback.

⑥ **Belief Update : $B_{t+1} = Update(B_t, I_t, Feedback_t)$ --- The agent updates its beliefs for the next cycle.**

Macro-Level Simulation: Dynamic Social Network

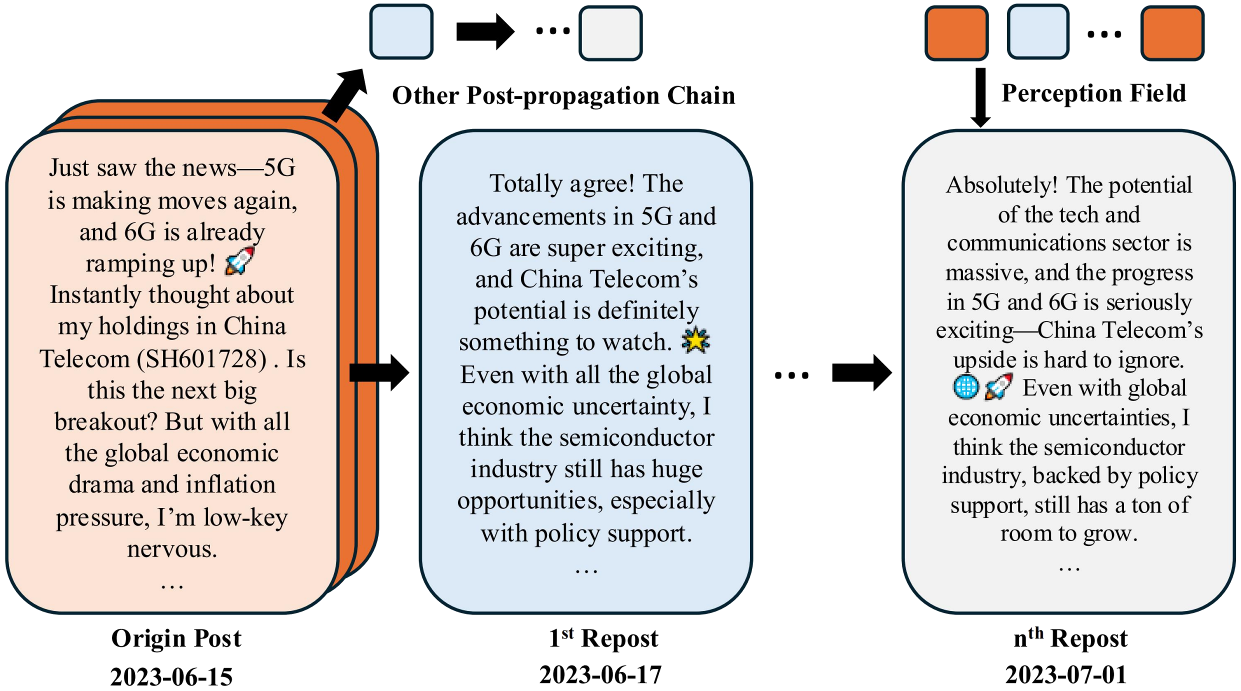


Constructing the Dynamic Social Network:

The social network evolves over time, reflecting changing user trading patterns and preferences.

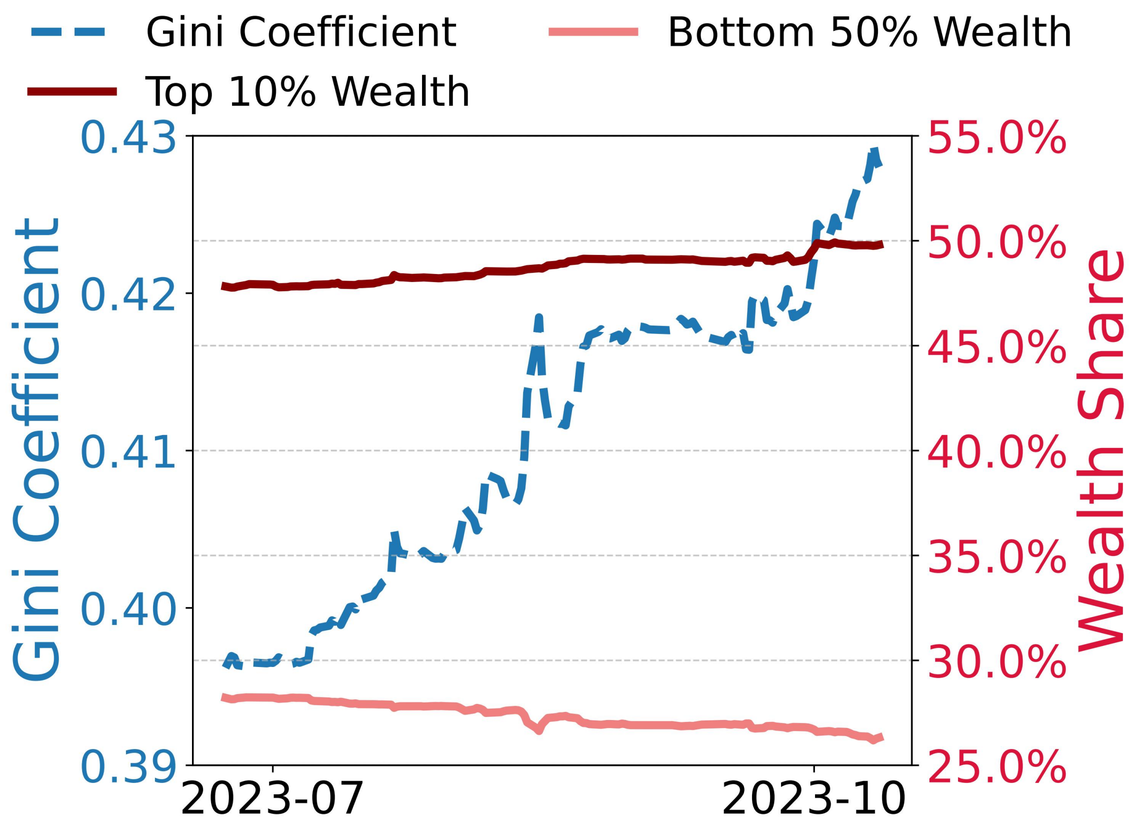
Information Aggregation Mechanism:

Information propagates through the network, with influential posts reaching a wider audience.



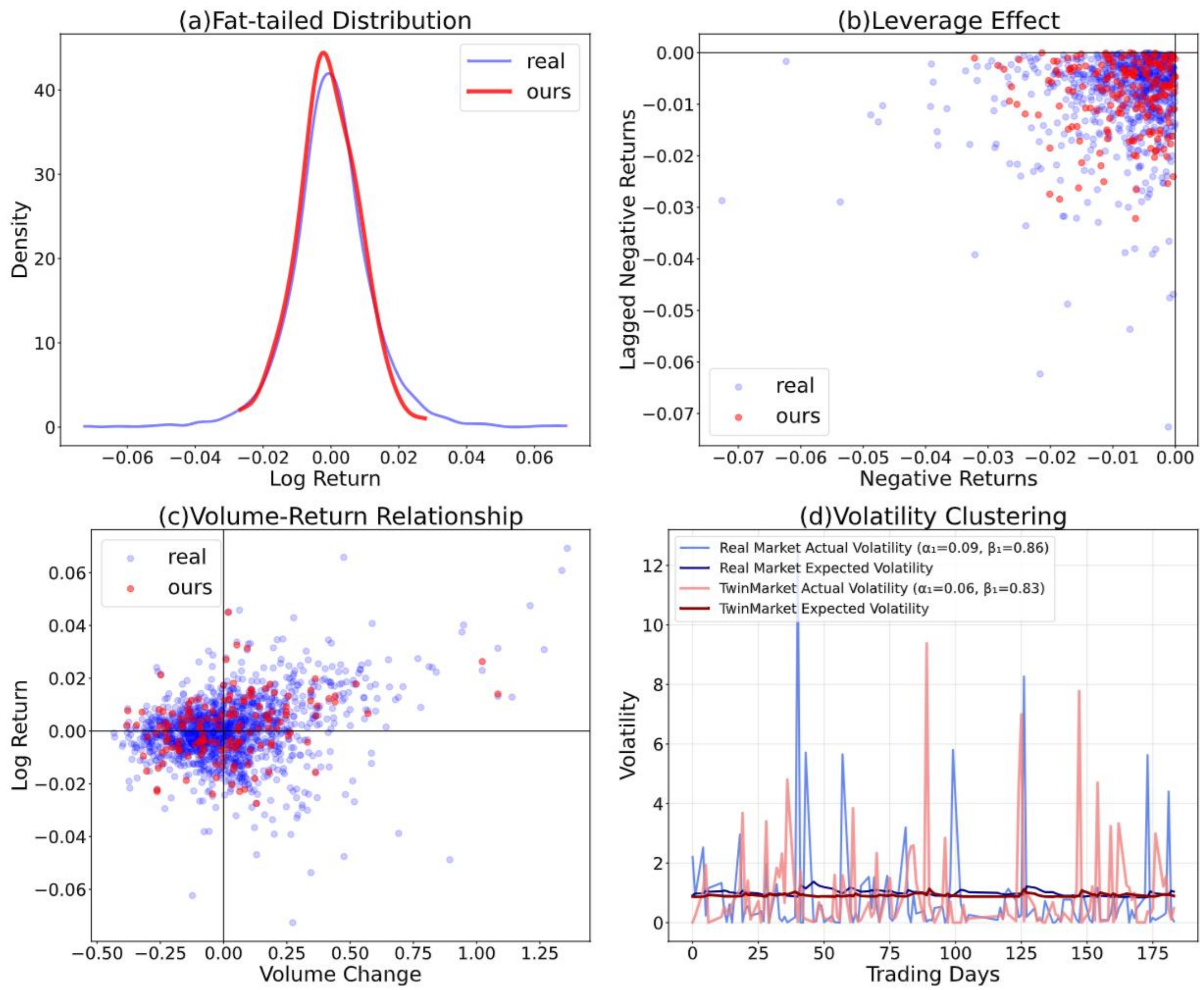
Micro-Level Validation

- Inequality in the stock market : Rising Gini coefficient, indicating widening wealth inequality.
- Trading Activity and Returns: Top 10% vs Bottom 50%



Performance	Avg. Turnover	Avg. Return
Top 10%	4.02%	6.65%
Bottom 50%	7.03%	-10.52%

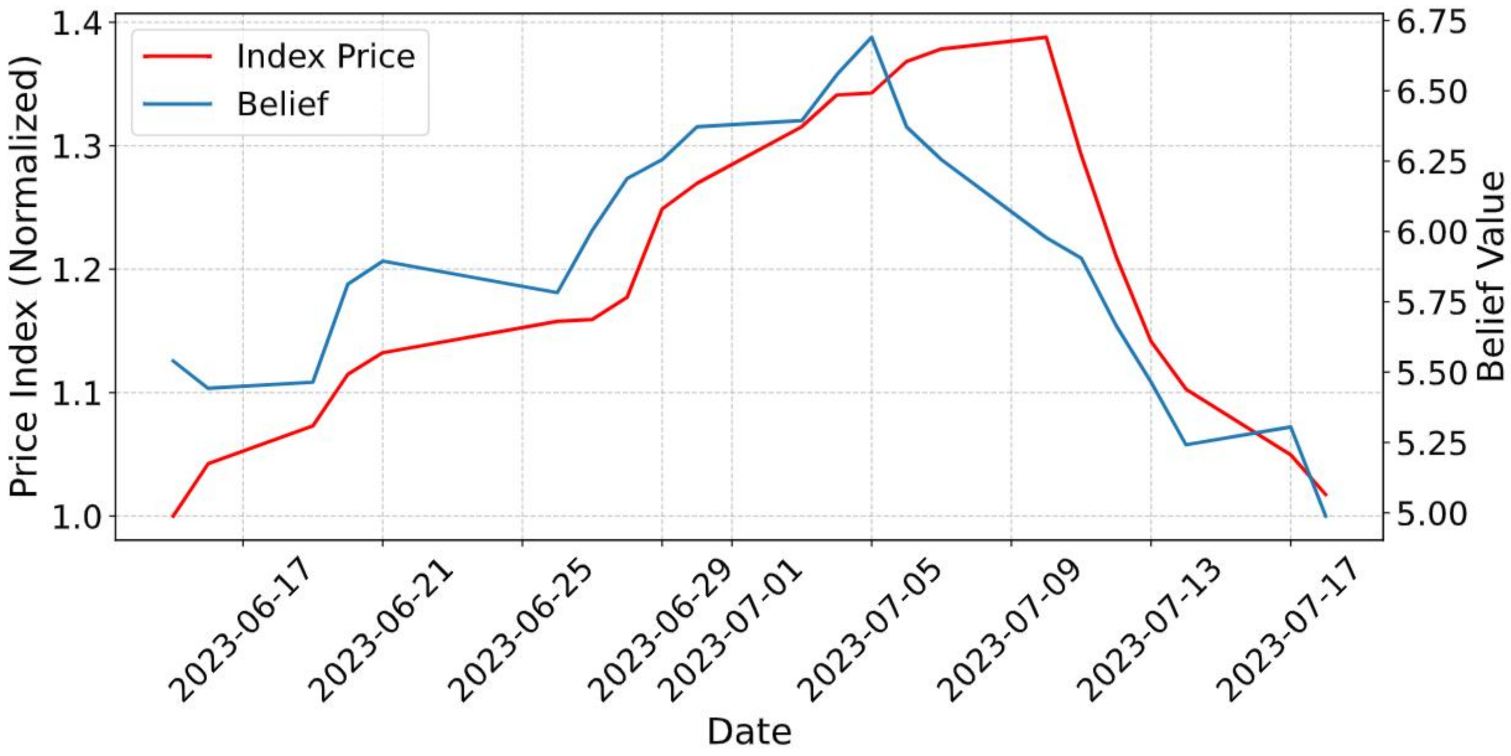
Macro-Level Validation



Simulation (red/ours) vs. Real (blue/real) markets: The stylized facts emerge naturally

Micro-Level Emergence – Bubbles rise and fall

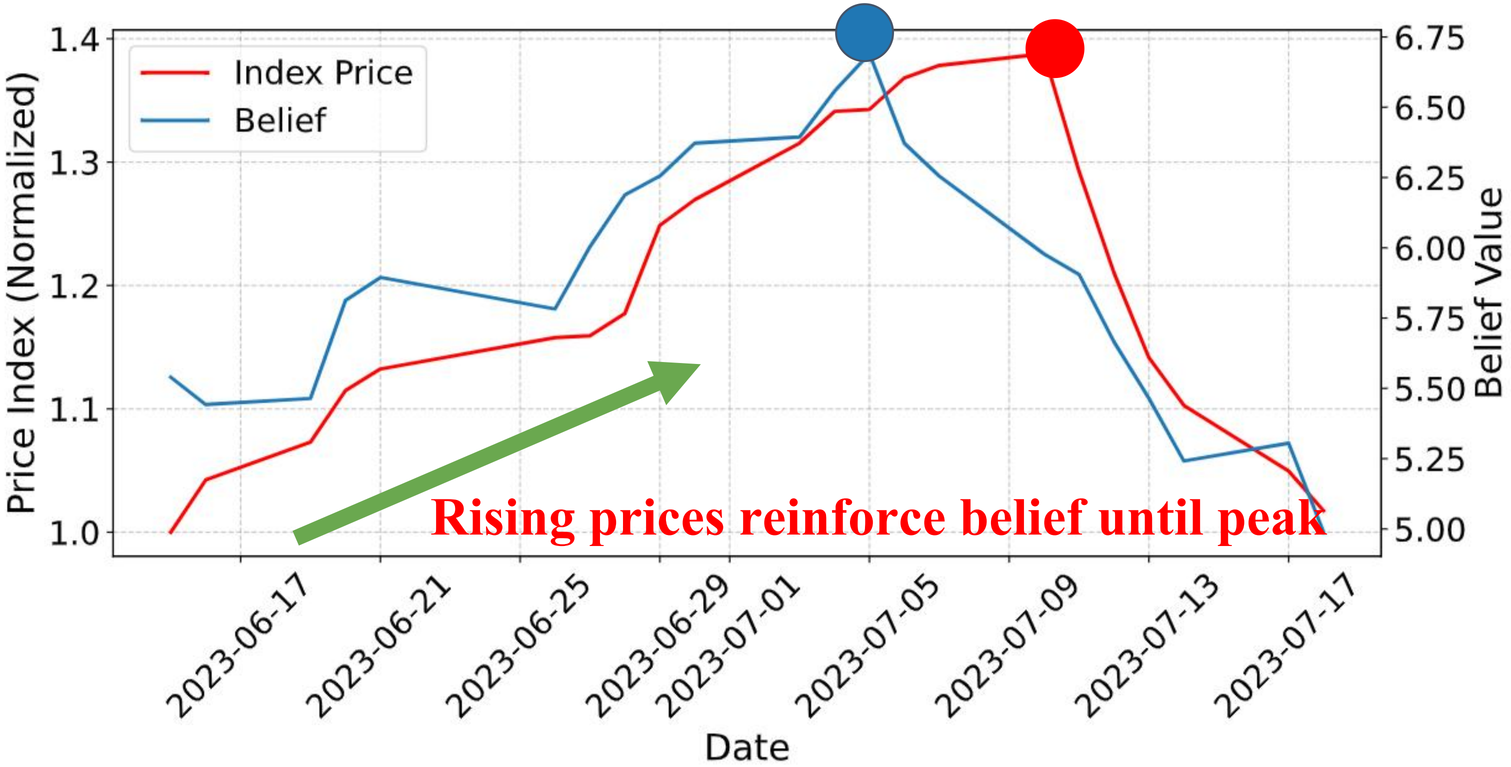
- Belief: Calculate evolving understanding of the market environment for each agent after trading
- Optimism drives increasing price



The rise and fall of market bubbles: People's beliefs and prices share similar trends

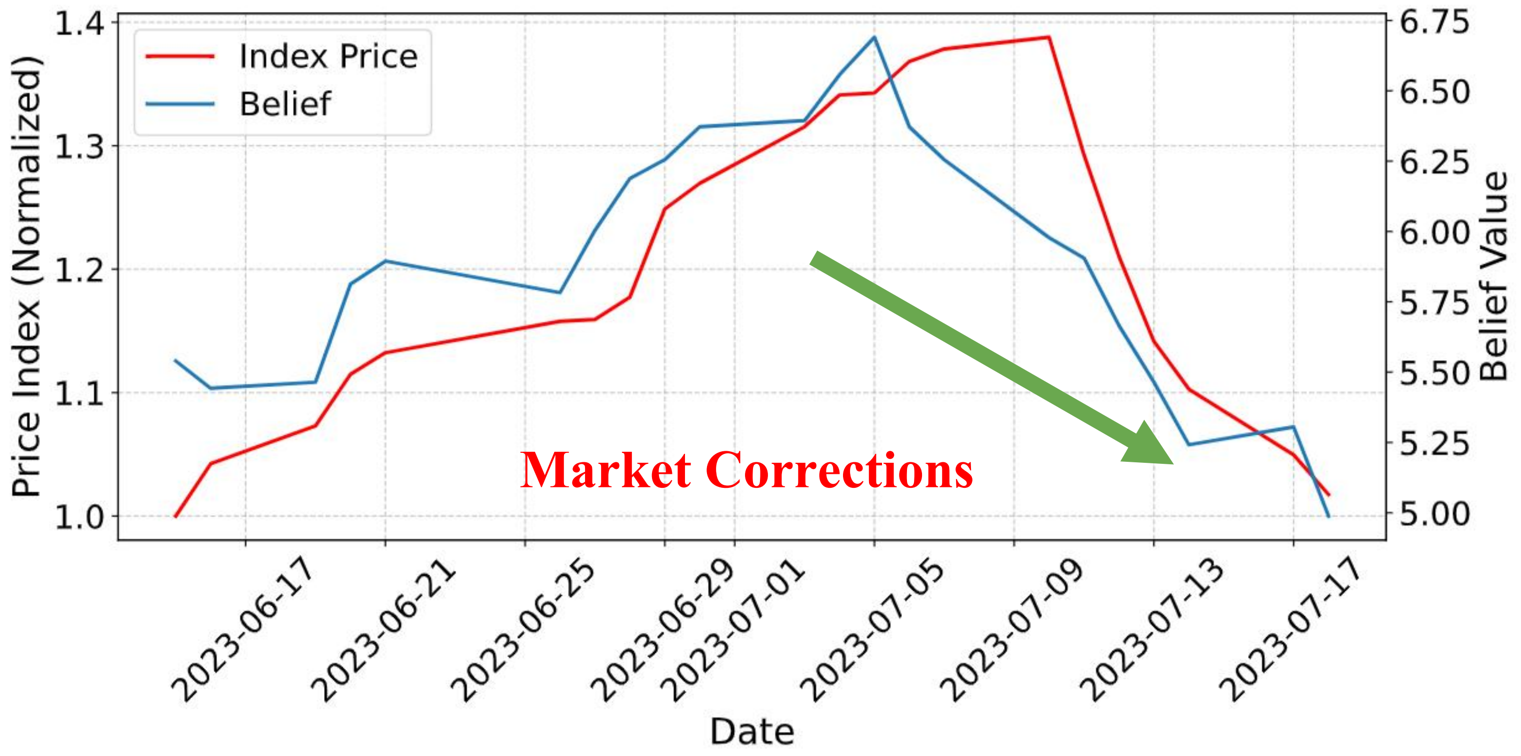
Micro-Level Emergence – Bubbles rise and fall

- Rising price creates a positive feedback loop



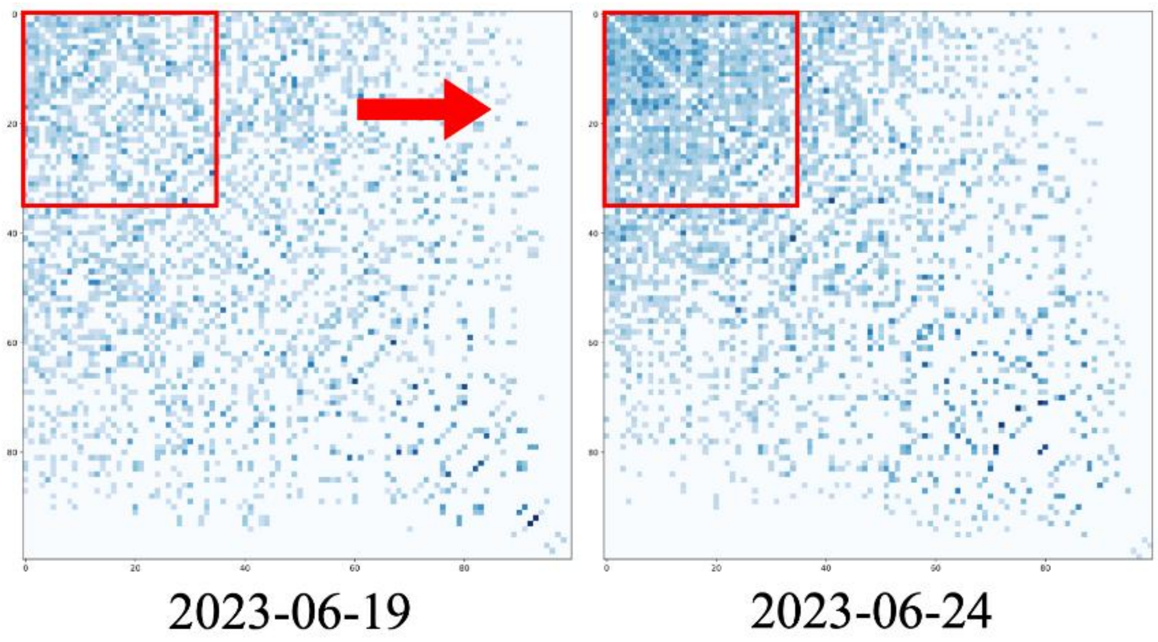
Micro-Level Emergence – Bubbles rise and fall

- Market corrections

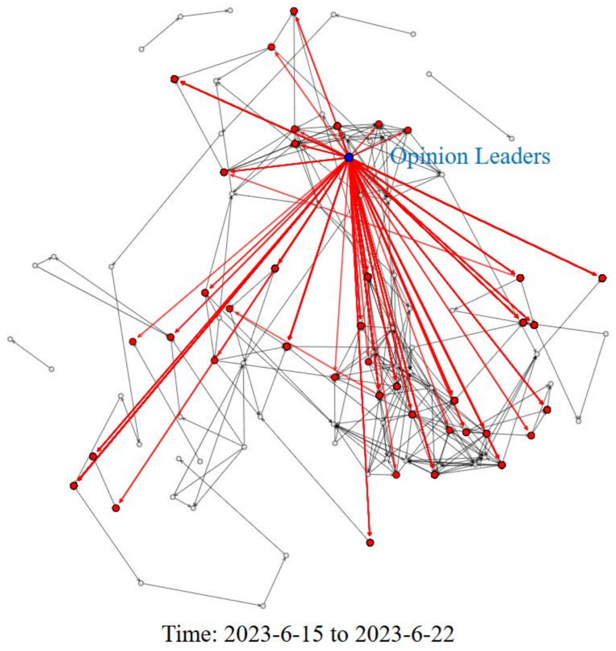


Macro-Level Emergence – Information Propagation

- **Setting: Select important news and push it to high-centrality users & Introduce rumors**
- Social Network Polarization
- Emergence of opinion leaders



Adjacency matrix view: Rumors lead to tighter behavioral clustering



Emergent Opinion Leaders (the center node)

Ablation Study

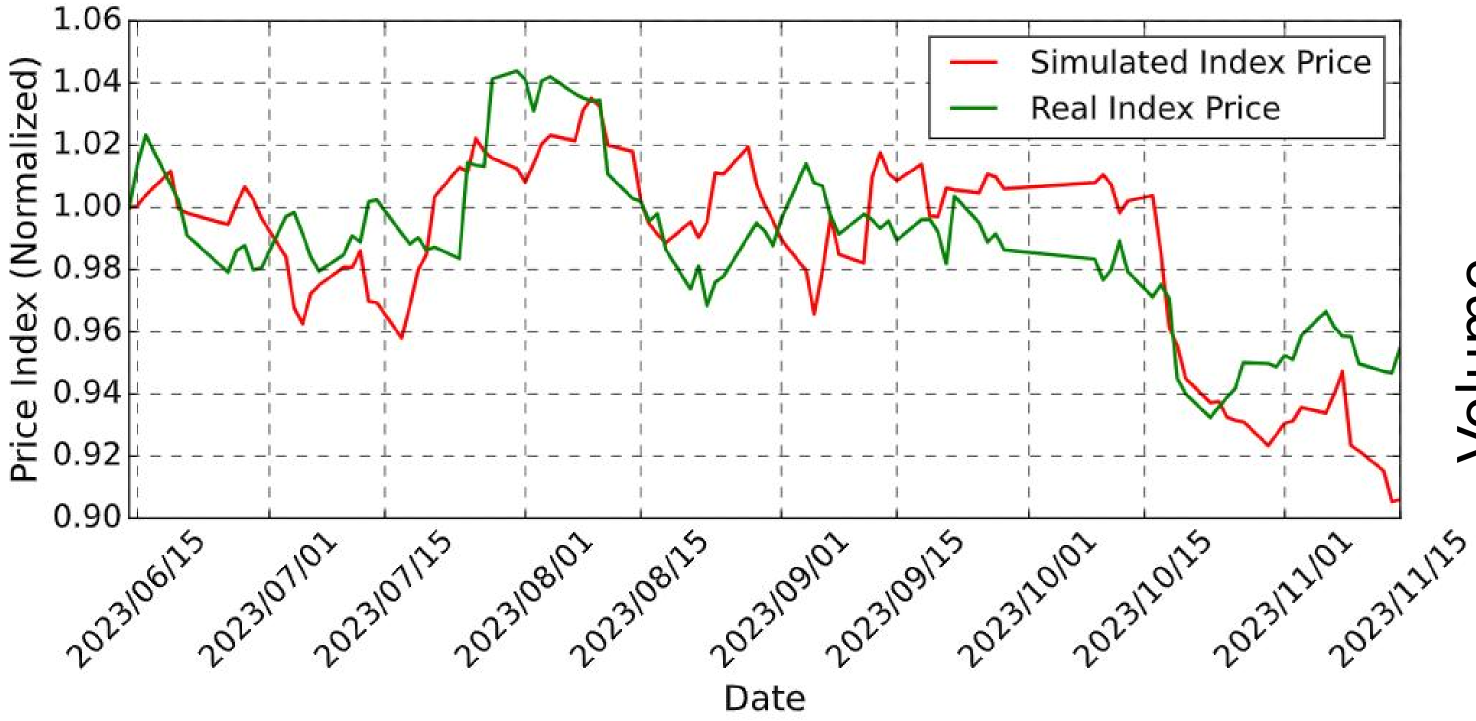
- **w/o BDI :** remove the belief-desire-intention module, making agents purely reactive
- **w/o Hetero.** : eliminate agent heterogeneity by assigning uniform strategies and biases

Table 5: Ablation study on the effects of the BDI framework and agent heterogeneity. ↑: higher is better, ↓: lower is better. Corr., RMSE, and MAE are computed on the daily normalized index price series between simulated outcomes and real-world data.

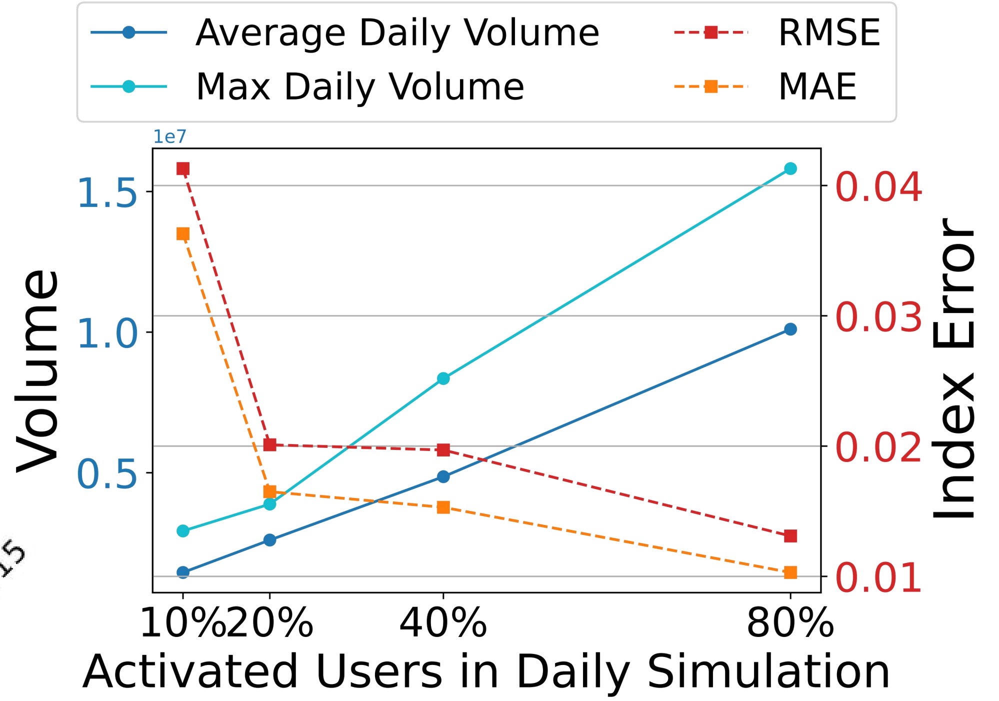
Model Variant	RMSE ↓	MAE ↓	Corr. ↑	Kurtosis ↑	Lev. Effect ↑	GARCH α ↑	GARCH β ↑
TwinMarket	**0.02**	**0.02**	**0.77**	**5.24**	**0.11**	**0.06**	**0.83**
TwinMarket w/o BDI	0.07	0.05	0.34	4.25	0.05	0.03	0.76
TwinMarket w/o Hetero.	0.09	0.08	-0.61	3.58	0.13	0.05	0.85

Scalability

- Scaled to 1000 agents
- Simulated index closely tracks real-world index (SSE 50)



1000-agent simulation (red)
closely tracks real-world (green) trend



Scaling Law:
Performance ∝ Volume

Contribution & Conclusion

- **Novel Framework for Social Simulation:** Integrating LLM agents with BDI cognitive architecture, market dynamics, and explicit social interaction for financial simulation.
- **Proof of Concept on Social Emergence:** Demonstrates how social influence and information flow drive emergent macro-phenomena (bubbles, polarization, turbulence) from micro-behaviors.
- **First Scaled Financial Simulation:** Replicates real-world stylized facts and scales to 1000+ agents, demonstrating both realism and scalability.

Thank You！