Hierarchical Multi-Agent Framework for Dynamic Macroeconomic Modeling Using Large Language Models

Extended Abstract

Zhixun Chen
University of Technology Sydney
Sydney, Australia
zhixun.chen@student.uts.edu.au

Zijing Shi
University of Technology Sydney
Sydney, Australia
zijing.shi@student.uts.edu.au

Yaodong Yang
Peking University
Beijing, China
yaodong.yang@pku.edu.cn

Meng Fang
University of Liverpool
Liverpool, United Kingdom
Meng.Fang@liverpool.ac.uk

Yali Du
King's College London
London, United Kingdom
yali.du@kcl.ac.uk

ABSTRACT

Large Language Models (LLMs) have demonstrated potential in simulating macroeconomic systems by integrating the agent-based models. Unlike rule-based systems or neural networks with fixed learning patterns, LLM agents capture the heterogeneity of economic actors. However, existing LLM-based simulation environments are generally static, maintaining constant government policies. In this study, we introduce a hierarchical framework that incorporates LLM economic agents and an LLM planner capable of formulating policies in response to evolving economic conditions. Utilizing the proposed framework, we further examine the simulated system's resilience to economic shocks by analyzing how economic agents respond to unforeseen events and how the planner adapts to mitigate these challenges. Our results indicate that the proposed framework improves the stability of the economic system and captures more dynamic macroeconomic phenomena, offering a precise and versatile simulation platform for studying real-world economic dynamics.

KEYWORDS

Agent-Based Model, Large Language Model, Macroeconomic Modeling

ACM Reference Format:
Zhixun Chen, Zijing Shi, Yaodong Yang, Meng Fang, and Yali Du. 2025. Hierarchical Multi-Agent Framework for Dynamic Macroeconomic Modeling Using Large Language Models: Extended Abstract. In *Proc. of the 24th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2025), Detroit, Michigan, USA, May 19 – 23, 2025*, IFAAMAS, 3 pages.

1 INTRODUCTION

The complexity of modern economies has prompted researchers to explore methods for simulating macroeconomic systems, with a particular focus on Agent-Based Models (ABMs) [6, 15]. Early models, relying on rule-based systems or neural networks, struggled to capture the behavioral heterogeneity of real economies [1, 17]. The introduction of neural networks has improved the flexibility and intelligence of modern ABM models by integrating deep learning methods such as reinforcement learning [16, 22].

However, generalization and robustness across different environments remain challenging. Recent advancements in Large Language Models (LLMs) have demonstrated advanced abilities such as reasoning and decision-making [2, 5, 8], enabling them to simulate complex economic activities like trade and resource allocation [9, 14, 19, 21]. EconAgent, which employs LLM agents for macroeconomic simulations, offers a more nuanced representation of economic agents but still treats agent interactions statically and overlooks dynamic government policies and economic shocks [12].

We propose a hierarchical, dynamic multi-agent framework that incorporates LLM agents to simulate economic policy planning and shock resilience. Our framework simulates adaptive agent behavior and evaluates the system's response to economic shocks by enabling LLM agents to adjust policies such as tax rates and inflation targets, thereby capturing interactions between heterogeneous agents and policy planners. Our experiments demonstrate that both LLM planners and agents can detect shocks, leading to swift recovery and enhanced system stability.

2 METHOD

2.1 Hierarchical Multi-Agent Framework

Building on the work of EconAgent [12], we introduce a macroeconomic simulation framework that employs agent-based modeling to capture complex economic interactions, as illustrated in Figure 1. The system consists of a planner and multiple heterogeneous economic agents operating on different timescales. Our framework extends previous efforts by incorporating dynamic planner decision-making and economic shocks to better mirror real-world conditions.

The planner optimizes macroeconomic variables—such as tax rates and inflation targets—on an annual basis, while the economic agents adjust their behavior monthly according to individual preferences and incentives. The planner P observes o_t based on: (1) macroeconomic indicators—such as unemployment rate, inflation rate, GDP growth, average wage, and economic equality—for the past L years, and (2) historical government policies over the past L years. Based on these observations, the planner sets tax rates

Proc. of the 24th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2025), Y. Vorobeychik, S. Das, A. Nowé (eds.), May 19 – 23, 2025, Detroit, Michigan, USA. © 2025 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org).

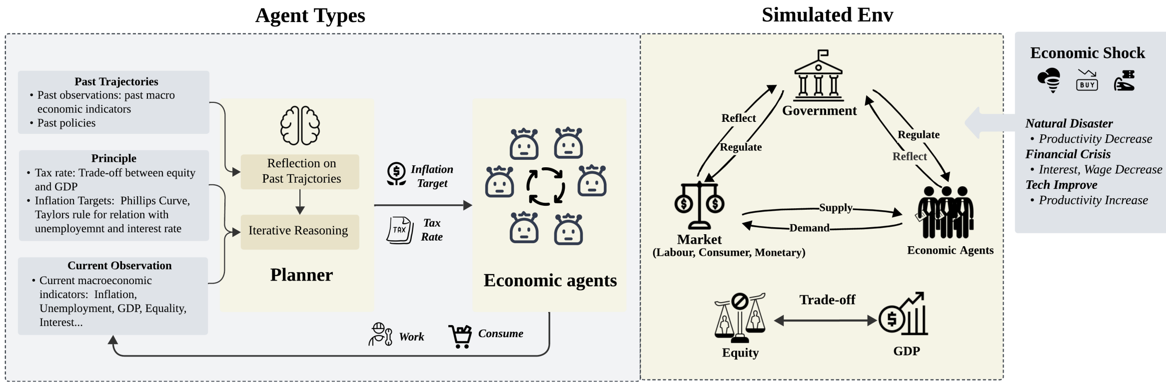

Figure 1: An overview of our approach.

for each income bracket $(\tau_1, \ldots, \tau_B)$, constrained between τ_{low} and τ_{high}, and determines the target inflation rate π_t for the coming year. For example, when the planner adjusts income tax rates, it affects the post-tax income that agents receive, which in turn alters their utility functions. This multi-agent learning problem, which naturally emerges in various economic and machine learning scenarios [4, 7], resembles a Stackelberg game [18], where the planner, acting as a leader, optimizes long-term economic outcomes while individual agents, as followers, make strategic decisions to maximize their own utilities within the constraints of these policies.

2.2 Grounding LLM as Planner

To effectively simulate the planner's role using an LLM, we incorporate reflective and iterative reasoning processes. The Principle and Observation Module provides macroeconomic guidelines for adjusting tax rates and setting inflation targets based on economic growth, inequality, and stability. Following Laffer curve theory [11], the planner optimizes tax rates to maximize redistribution without hindering economic activity. Additionally, the Taylor Rule [3, 20] and the Phillips Curve [13] guide the planner in balancing inflation and unemployment to enhance social welfare. The Reflection Module reviews historical trajectories by retrieving L prior action-observation pairs, facilitating continuous policy improvement. By analyzing past trajectories, fundamental economic principles, and current observations, the LLM-based planner iteratively refines its decision-making, ensuring adaptive and robust policy formulation.

3 EXPERIMENTS

Our experiments explore how a planner can control key macroeconomic indicators—such as GDP growth, unemployment, inflation, and equality—through the implementation of tax policies and inflation targets. We set the number of agents to 50. Figure 2 illustrates the system's economic situation during a natural disaster, where the productivity factor A drops sharply, triggering price inflation and reducing GDP. In our method, the unemployment rate spikes to 20% and societal equality falls below 50%. As productivity recovers after five years, inflation stabilizes around 1%, unemployment decreases to 10%, and equality rises above 50%, indicating economic recovery.

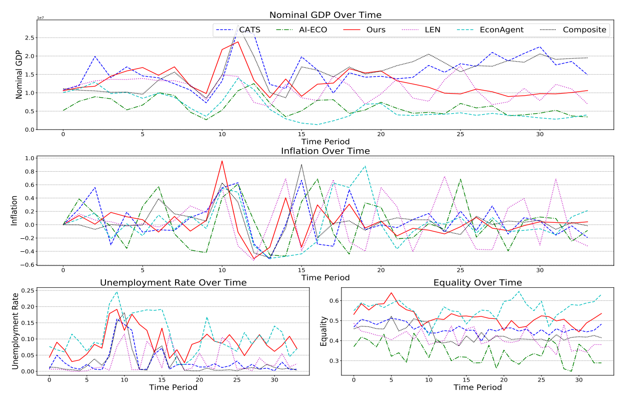

Figure 2: Variation of annual macroeconomic indicators under an economic shock caused by a natural disaster. The shock occurs in the eighth year of the simulation.

In contrast, the EconAgent environment maintains high societal equality immediately after the shock. However, this hinders economic recovery post-disaster [10]. Rule-based models recover GDP better but show equality levels below 50% (in some cases below 40%), suggesting uneven recovery benefits. Additionally, these models experience extreme inflation fluctuations between -60% and 60%. AI-ECO exhibits 35% equality and 50% unemployment, resulting in consistently low GDP.

4 CONCLUSION

In conclusion, this work advances macroeconomic simulation with the hierarchical framework of economic agents and a dynamic policy planner. Unlike static models, our planner adapts to evolving conditions, aligning better with real-world complexities. By utilizing the principle and reflection modules, it effectively handles economic shocks and enhances social welfare, resulting in a resilient system. The study shows that our method captures intricate economic behaviors, making it a valuable platform for exploring macroeconomic policies. This work highlights the potential of LLMs in simulating complex economic systems, opening new pathways for analyzing responsive policymaking and economic phenomena.

REFERENCES

[1] Shu-Heng Chen, Chia-Ling Chang, and Ye-Rong Du. 2012. Agent-based economic models and econometrics. *The Knowledge Engineering Review* 27, 2 (2012), 187–219.

[2] Xiong-Hui Chen, Ziyan Wang, Yali Du, Shengyi Jiang, Meng Fang, Yang Yu, and Jun Wang. 2025. Policy learning from tutorial books via understanding, rehearsing and introspecting. *Advances in Neural Information Processing Systems* 37 (2025), 18940–18987.

[3] Herbert Dawid and Domenico Delli Gatti. 2018. Agent-based macroeconomics. *Handbook of computational economics* 4 (2018), 63–156.

[4] Yali Du, Joel Z Leibo, Usman Islam, Richard Willis, and Peter Sunehag. 2023. A review of cooperation in multi-agent learning. *arXiv preprint arXiv:2312.05162* (2023).

[5] Meng Fang, Shilong Deng, Yudi Zhang, Zijing Shi, Ling Chen, Mykola Pechenizkiy, and Jun Wang. 2024. Large language models are neurosymbolic reasoners. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 38. 17985–17993.

[6] J Doyne Farmer and Duncan Foley. 2009. The economy needs agent-based modelling. *Nature* 460, 7256 (2009), 685–686.

[7] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems*, Vol. 27. https://proceedings.neurips.cc/paper_files/paper/2014/file/5ca3e9b122f61f8f06494c97b1afccf3-Paper.pdf

[8] Xuanfa Jin, Ziyan Wang, Yali Du, Meng Fang, Haifeng Zhang, and Jun Wang. 2025. Learning to discuss strategically: A case study on one night ultimate werewolf. *Advances in Neural Information Processing Systems* 37 (2025), 77060–77097.

[9] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2022. Large language models are zero-shot reasoners. *Advances in neural information processing systems* 35 (2022), 22199–22213.

[10] Simon Kuznets. 2019. Economic growth and income inequality. In *The gap between rich and poor*. Routledge, 25–37.

[11] Arthur B Laffer. 2004. The Laffer curve: Past, present, and future. *Backgrounder* 1765, 1 (2004), 1–16.

[12] Nian Li, Chen Gao, Mingyu Li, Yong Li, and Qingmin Liao. 2024. Econagent: large language model-empowered agents for simulating macroeconomic activities. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 15523–15536.

[13] Edmund S Phelps. 1967. Phillips curves, expectations of inflation and optimal unemployment over time. *Economica* (1967), 254–281.

[14] Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. 2024. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems* 36 (2024).

[15] Leigh Tesfatsion. 2006. Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics* 2 (2006), 831–880.

[16] Alexander Trott, Sunil Srinivasa, Douwe van der Wal, Sebastien Haneuse, and Stephan Zheng. 2021. Building a foundation for data-driven, interpretable, and robust policy design using the ai economist. *arXiv preprint arXiv:2108.02904* (2021).

[17] Sander van der Hoog. 2017. Deep learning in (and of) agent-based models: A prospectus. *arXiv preprint arXiv:1706.06302* (2017).

[18] Heinrich Von Stackelberg. 2010. *Market structure and equilibrium*. Springer Science & Business Media.

[19] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems* 35 (2022), 24824–24837.

[20] Sarah Wolf, Steffen Fürst, Antoine Mandel, Wiebke Lass, Daniel Lincke, Federico Pablo-Marti, and Carlo Jaeger. 2013. A multi-agent model of several economic regions. *Environmental modelling & software* 44 (2013), 25–43.

[21] Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. 2024. Tree of thoughts: Deliberate problem solving with large language models. *Advances in Neural Information Processing Systems* 36 (2024).

[22] Stephan Zheng, Alexander Trott, Sunil Srinivasa, David C Parkes, and Richard Socher. 2022. The AI Economist: Taxation policy design via two-level deep multiagent reinforcement learning. *Science advances* 8, 18 (2022), eabk2607.