Large Language Model-Empowered Agents for Simulating Macroeconomic Activities

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Abstract

The advent of the Web has brought about a paradigm shift in traditional economics, particularly in the digital economy era, enabling the precise recording and analysis of individual economic behavior. This has led to a growing emphasis on data-driven modeling in macroeconomics. In macroeconomic research, Agent-based modeling (ABM) emerged as an alternative, evolving through rulebased agents, machine learning-enhanced decision-making, and, more recently, advanced AI agents. However, the existing works are suffering from three main challenges when endowing agents with human-like decision-making, including agent heterogeneity, the influence of macroeconomic trends, and multifaceted economic factors. Large language models (LLMs) have recently gained prominence in offering autonomous human-like characteristics. Therefore, leveraging LLMs in macroeconomic simulation presents an opportunity to overcome traditional limitations. In this work, we take an early step in introducing a novel approach that leverages LLMs in macroeconomic simulation. We design prompt-engineeringdriven LLM agents to exhibit human-like decision-making and adaptability in the economic environment, with the abilities of perception, reflection, and decisionmaking to address the abovementioned challenges. Simulation experiments on macroeconomic activities show that LLM-empowered agents can make realistic work and consumption decisions and emerge more reasonable macroeconomic phenomena than existing rule-based or AI agents. Our work demonstrates the promising potential to simulate macroeconomics based on LLM and its humanlike characteristics.

1 Introduction

The advent of the Web has indeed altered the research paradigm in traditional economics [24]. Specifically, in the digital economy era, each individual's economic behavior can be well recorded and analyzed, leading to an increasing emphasis on individual data-driven modeling in macroeconomics. These data may include consumption habits, online shopping, social media activity, search histories, and more, which economists can utilize to understand better individual economic behavior rather than relying solely on traditional macroeconomic indicators [39].

Economic research in macroeconomics aims to analyze and predict economic variables quantitatively. Early empirical statistical models, such as the Phelps Model [36], and the work of Kydland and Prescott [27], focused on data-driven analysis and policy outcome prediction. Dynamic Stochastic General Equilibrium (DSGE) models [9] were introduced to capture economic dynamics but assumed a perfect world. Agent-based modeling (ABM) emerged as a promising alternative, allowing diverse agents and institutions to interact without assuming a predetermined equilibrium [15]. ABM accommodates nonlinear behaviors and allows policymakers to simulate various policy scenarios and assess their economic impacts. The evolution of ABM in macroeconomics can be divided into three stages: early models [43, 6] relied on rule-based agent behavior but oversimplified interactions; integration of machine learning techniques improved agent decision-making with more data-driven behavior [19, 15]; recent advancements involve neural networks, deep learning, and reinforcement learning to create sophisticated and adaptive AI agents [45, 53].

However, the macroeconomic simulation still suffers the critical challenges from three aspects. First, the intrinsic heterogeneity of agents plays a pivotal role in the emergence of macroeconomic phenomena, posing significant challenges for effective modeling. Second, when delving into the dynamic interplays within labor, consumption, and financial markets, capturing the impacts of overarching macroeconomic trends on individual agent decision-making becomes a hard task. Third, there are multifaceted economic factors shaping decision-making processes, such as the expected income, the tax paid, *etc*.

Recently, the field of artificial intelligence has seen the rise of large language models (LLMs) [52]. Building on this advancement, agents powered by these LLMs have been exhibiting an ability to interact, reason, and make decisions. LLM-based agents have the potential to overcome traditional limitations by offering more realistic and adaptable decisions, thereby providing a more comprehensive simulation. First, the LLM agent is able to behave autonomously, i.e., adaptively react and perform tasks based on the environment without explicit instructions [42, 50]. Second, the LLM agent has enough intelligence that it can respond like a human and even actively take actions with self-oriented planning and scheduling [46, 48]. Last, the LLM agent has the ability to interact and communicate with humans or other AI agents [34].

In this study, we introduce a novel approach to macroeconomic simulation by leveraging large language models. First, we build a detailed simulation environment that mirrors the essential components and dynamics of a real-world economy. In this environment, we deploy a prompt-engineeringdriven LLM agent designed with the abilities of perception, reflection, and decision-making based on the context of real-world economic environments. Specifically, we enrich agents with heterogeneous real-world profiles and characterize real economic environments in the perception module to foster the emergence of macroeconomic behaviors, addressing the first challenge. To make agents grasp market dynamics, we design a memory module to simulate the impact of broad macroeconomic trends on agents' decision-making. Last, by harnessing the LLM's semantic perception, we prompt the agent to make decisions considering multiple economic variables in the action module without necessitating pre-defined rules.

During our experiments, classic macroeconomic phenomena are reproduced and more reasonable compared to traditional rule-based or AI agents, such as inflation in the consumption market and unemployment rate in the labor market. We also observed that the LLM agents exhibited human-like decision-making patterns, echoing the intricacies of human economic behavior. These agents showcased swift adaptability when meeting shifts in the internal environment.

The contribution of this paper can be summarized as follows.

- In this paper, we take the pioneering step of integrating large language models into the domain of macroeconomic simulations, bridging two seemingly disparate fields into a cohesive research avenue.
- We construct an environment and design LLM-empowered agents, which not only emulate realworld economic actors but also emerge classic macroeconomic phenomena.
- The results show that our approach not only enhances the realism and depth of macroeconomic simulations but also provides a promising avenue for future research, potentially reshaping how we study and understand the intricacies of global economies.

2 Related Work

2.1 Simulation in Economy Research

Economic research, especially for macroeconomics, tries to obtain quantitative analysis or prediction for the economic variables. The earliest works of empirical statistical models [21], such as Phelps Model [36], study the data-driven analysis for the macroeconomic phenomenon, by revealing the relations between some critical variables. Kydland and Prescott [27] designed a computational model for predicting the outcome of the policy. After that, Dynamic Stochastic General Equilibrium (DSGE) models [9], are designed to capture the dynamics of various economic variables, such as output, inflation, consumption, and investment, while accounting for the uncertainty and randomness inherent in economic processes. However, as pointed out by [15], "these models assume a perfect world, and by their very nature rule out crises of the type we are experiencing now."

Different from these models, Agent-based modeling (ABM) is a more promising solution, in which diverse agents and institutions interact based on rules or computational models, avoiding the assumption of a predetermined economic equilibrium. These models allow for a wide range of nonlinear behaviors, enabling policymakers to simulate different policy scenarios and quantitatively assess their impacts on the economy. The paradigm of agent-based modeling in macroeconomics can also be regarded as a simulation-based approach, of which the related research can be divided into three stages: In the early stages of agent-based modeling [43, 6], models were primarily rule-based, with agents following predetermined sets of rules. These models were characterized by their simplicity and reliance on heuristic decision rules. While they provided valuable insights into emergent system behaviors, they often oversimplified agent behavior and interactions. After that, with the progress of machine learning, researchers integrated machine learning techniques into agent-based models. To be specific, machine learning algorithms were employed to enhance agent decision-making processes, allowing for more data-driven and realistic agent behaviors [19, 15]. However, these models still had limitations in capturing the full complexity of economic systems. Recently, researchers have leveraged neural networks, deep learning, and reinforcement learning to create more sophisticated and adaptive AI agents [45, 53].

In this work, we explore leveraging large language models, which are considered as sparks of artificial general intelligence (AGI) to construct agents for simulation-based research on macroeconomics.

2.2 Large Language Model-empowered Agents

As mentioned above, the simulation system has widely utilized the paradigm of agent-based modeling. Recently, large language models such as ChatGPT [33], LLaMA [44], Alphca [41], and GLM [51] have achieved a huge breakthrough, considered as a sparkle of artificial general intelligence (AGI) [7, 49]. To be specific, these large language models trained with large-scale corpus have shown human-level abilities in three aspects, and provide the basis for using LLM to construct agents for simulation [46, 48].

First, the LLM agent is able to adaptively react and perform tasks based on the environment without predefined explicit instructions [42, 50]. In addition, during the simulation process, the LLM agent can even burst new ideas, solutions, goals, etc, [16]. For example, AutoGPT can automatically schedule plans when given a set of available tools and the final task goal, exemplifying the significant potential of LLMs in constructing autonomous agents. BabyAGI [50] created an LLM-driven script running an infinite loop, which continuously maintains a task list, in which each task is completed the task by ChatGPT API [33] based on the task context. Second, the LLM agent has enough intelligence that it can respond like a human and even actively take actions with self-oriented planning and scheduling [46, 48]. The environment input is not limited to the textual input; instead, the recent multi-modal fusion methods can feed other types of information, such as image or audio, to the LLM agent [54]. The action space of the LLM agent is neither limited to texts, for which the tool usage and internal action module allow the agent to take various actions [38]. Last, the LLM agent has the ability to interact and communicate with humans or other AI agents [34]. In the simulation, especially agent-based simulation, the communication ability promotes the individual simulation to community-level [20]. For an LLM-driven agent, it can generate texts, which can be received and understood by another agent, which provide the basis for interpretable communication among agents or between humans and agents [34]. Moreover, the simulation at the community level requires heterogeneity in agents, and the LLM agents can well meet the requirements with different prompts or demonstrations for playing different roles in society [37].

With the three aspects of strong abilities, LLM agents have been widely used in many areas, including social science [35, 30, 29, 34, 26, 31, 26, 17, 23], natural science [3, 4], etc. Social science is one of the most promising areas for adopting LLM agents for simulation, which is the science of society and social activities. For example, Social Simulacra [35] simulates an online social community and explores the potential of utilizing agent-based simulations to aid decision-makers in improving community regulations. Some other works [30, 29] investigate the potential impacts of different behavioral characteristics of LLM-based agents in social networks. Generative Agents [34] and



Figure 1: The illustration of our simulation framework and large language model-based agents.

AgentSims [31] construct multiple agents in a virtual town to simulate human daily life. SocialAI School [26] employs LLM-based agents to simulate and investigate the fundamental social cognitive skills during the course of child development. S^3 [17] builds a social network simulator, focusing on the propagation of information, emotion, and attitude. CGMI [23] is a framework for multi-agent simulation. CGMI maintains the personality of the agents through a tree structure and constructs a cognitive model. The authors simulated a classroom scenario using CGMI.

It is worth mentioning there are some works that consider the use of LLM in economic research. Horton *et al.* [22] studied the bias in decision-making with several decision-making experiments in the economy. Bran *et al.* [5] studied some individual features of LLM agents, such as willing-topay. Bybee *et al.* [8] studied the LLM agent's ability to understand the financial and macroeconomic variables based on news from the Wall Street Journal. In short, these existing works have conducted several attempts to evaluate LLM's economic characteristics, such as rationality, and the perception of investor sentiment. However, these works only consider individual one-step behavior, without experimenting on multi-step behaviors within a multi-agent simulation environment, which is the focus of our work.

3 System Overview

In this section, we present the overall system of the macroeconomic simulation. It follows the wellacknowledged simulation model and provides an environment for large language model-empowered agents. The overall framework is illustrated in Figure 1. Macroeconomics encompasses four components: labor, consumption, financial markets, and government taxation, covering the primary components of existing macroeconomic simulations. In this work, we simulate the two most critical decisions individuals make in real life: work and consumption, which subsequently influence the fiscal revenues of the government and impact the dynamics of labor and consumption markets. Accordingly, banks adjust interest rates based on market inflation or deflation. In the following, we shed light on the system's design, mechanics, and anticipated capabilities, as well as the challenges of simulating real-world agent decisions.

3.1 System Design and Mechanics

Our framework encompasses 1) agents' labor supply and consumption decisions [18, 47, 10], 2) government taxation [53, 45, 10], 3) dynamics in the labor and consumption markets [28, 12, 11], and 4) adjustments in bank interest rates [47, 10]. Important notations are shown in Table 1.

3.1.1 Agent Decisions

Labor supply and consumption are necessary agent decisions in macroeconomic simulations. In our system, each simulation step indicates one month, in which agent i decides,

• whether to work $l_i \sim Bernoulli(p_i^w)$, where p_i^w is the work propensity. If they decide to work $(l_i = 1)$, they receive a monthly wage as the income, which varies among agents. Each agent is initialized with an hourly wage w_i following the Pareto distribution [53], and the monthly wage v_i is calculated by multiplying 168 hours (21 working days at 8 hours/day [28]). Those who abstain from work $(l_i = 0)$ have an income of zero.

Table 1: Important notations.						
N	The number of agents					
p_i^w, l_i	Work propensity, whether to work					
p_i^c	Consumption propensity					
$w_i, v_i, z_i, \hat{z}_i, s_i$	Hourly wage, monthly wage (expected in- come),					
	income, post-tax income, savings					
Р	The price of essential goods.					
r, π, u	Interest rate, inflation rate, unemployment rate					
r^n, π^t, u^n	Natural interest rate, target inflation rate, natural unemployment rate					

• the consumption propensity p_i^c , indicating the proportion of their wealth (including their current savings and income in this month) they wish to spend for essential goods.

As one of the challenges of simulating agent decisions and emerging coherent macroeconomic phenomena, there are multifaceted economic factors influencing decisions, such as the expected income, the tax paid, *etc.* However, conventional simulations typically model a limited number of factors via pre-defined equations [28, 18, 47].

3.1.2 Government Taxation

The government assumes the responsibility of taxation and provision of public services in society, as well as fiscal redistribution to ensure social equity. Taxes are collected from all the agents' income¹. The progressive tax for income z_i is calculated as follows,

$$T(z_i) = \sum_{k=1}^{B} \tau_k \left((b_{k+1} - b_k) \mathbf{1} [z_i > b_{k+1}] + (z_i - b_k) \mathbf{1} [b_k < z_i \le b_{k+1}] \right),$$
(1)

where b_k is the k-th tax bracket, τ_k is corresponding tax rate, and $\mathbf{1}[\cdot]$ is indicator function. The tax brackets and rates are set as the 2018 U.S. Federal tax schedule.

The tax revenue is then evenly redistributed among all the agents. Therefore, the post-tax income is

$$\hat{z}_i = z_i - T(z_i) + z^r = z_i - T(z_i) + \frac{1}{N} \sum_{j=1}^N T(z_j),$$
(2)

where z^r indicates the redistribution. The individual savings for the agent are then updated as follows,

$$s_i \leftarrow s_i + \hat{z}_i \tag{3}$$

3.1.3 Productivity and Consumption

Incorporating agent decisions and government taxation, we simulate labor and consumption market dynamics based on economic principles. First, working agents contribute 168 hours of productivity monthly, translating to the production of essential goods². The inventory of goods G is then updated as,

$$G \leftarrow G + S = G + \sum_{j=1}^{N} l_j \times 168 \times A, \tag{4}$$

where S denotes the production volume from agents' labor supply, and A is a universal productivity. As for the consumption, the total demand of goods is,

$$D = \sum_{j=1}^{N} d_j = \sum_{j=1}^{N} \frac{c_j}{P} = \sum_{j=1}^{N} \frac{p_j^c s_j}{P},$$
(5)

¹We only consider income tax in this work and leave other taxes for future work, such as value-added tax.

²Note that we leave the simulation of firms as future work.

where d_j is the intended demand of agent j, c_j is the intended consumption, s_j is current savings, and P is the price of essential goods. Furthermore, both labor and consumption markets evolve based on the imbalance between supply and demand. Specifically, the imbalance is defined as,

$$\bar{\varphi} = \frac{D - G}{\max(D, G)},\tag{6}$$

When the essential goods are in shortage, *i.e.*, the supply can not meet the demand, the worker's wage should be increased to stimulate production. Due to the rise in labor costs for firms, they will also increase the goods price to ensure a certain profit margin [28, 10, 47]. The hourly wage is adjusted as follows,

$$w_i \leftarrow w_i \times (1 + \varphi_i), \varphi_i \sim \begin{cases} Uniform(0, \alpha_w \bar{\varphi}), & \bar{\varphi} \ge 0\\ Uniform(\alpha_w \bar{\varphi}, 0), & \bar{\varphi} < 0 \end{cases},$$
(7)

and the price is adjusted as follows,

$$P \leftarrow P \times (1 + \varphi_P), \varphi_P \sim \begin{cases} Uniform(0, \alpha_P \bar{\varphi}), & \bar{\varphi} \ge 0\\ Uniform(\alpha_P \bar{\varphi}, 0), & \bar{\varphi} < 0 \end{cases},$$
(8)

where α_w and α_P are the maximum rate of change when adjusting the wage and price, respectively. We also simulate the dynamics of goods consumption. Specifically, an agent *j* is randomly selected to consume essential goods, and real consumption goods and money are limited by current inventory of goods,

$$\hat{d}_j = \min(d_j, G), \hat{c}_j = \hat{d}_j \times P \tag{9}$$

which means the demand is met if, and only if, there is a sufficient supply. The inventory of total goods also decreases,

$$G \leftarrow G - \hat{d}_j.$$
 (10)

The process continues until every agent has consumed goods once.

3.1.4 Financial Market

Annually, the savings of each agent increase based on the interest rate set by the bank,

$$s_i \leftarrow s_i \times (1+r). \tag{11}$$

Furthermore, in the first month of each year, the bank adjusts the interest rate based on the inflation in the consumption market and the unemployment rate in the labor market. Specifically, we adopt the widely-used Taylor rule to set the interest rate [47, 10],

$$r = \max(r^{n} + \pi^{t} + \alpha^{\pi}(\pi - \pi^{t}) + \alpha^{u}(u^{n} - u), 0),$$
(12)

where r^n and u^n indicate the natural interest rate and unemployment rate, respectively. Besides, π^t is the target inflation rate. The interest rate is adjusted adaptively according to annual inflation rate π and unemployment rate u, where α^{π} and α^{u} denote inflation and unemployment adaptation coefficients, respectively. We define the inflation and unemployment rate as follows,

$$\pi = \frac{\bar{P}_n - \bar{P}_{n-1}}{\bar{P}_{n-1}}, u = \frac{\sum_{m=1}^{12} \sum_{j=1}^{N} (1 - l_j)}{12N},$$
(13)

where P_n is the average goods price over the *n*-th year, and *m* denotes the *m*-th month.

When considering the dynamics of labor, consumption, and financial markets, the influence of these macroeconomic trends on agent decision-making is also seldom considered, raising the second challenge. Moreover, the heterogeneity of agents, which is vital for the emergence of macro phenomena, is also challenging to handle. Existing models often lack of flexibility to simulate heterogeneous agents and assume one or a few representative decision-making rules [2].

Leveraging the semantic understanding of LLM, the automatic perception of economics in the real world, and memory and reflection capabilities, we can achieve human-like simulation of agent decisions.

3.2 System Capabilties

- **Replication of economic phenomena**. Our system encapsulates the essence of economic behaviors and dynamics, such as labor market inflation and financial market fluctuations, as well as how people respond to them [15, 10, 2]. Classic and important economic phenomena can be replicated under reasonable agent decision-making.
- Extensibility. Beyond mere replication of economic phenomena, it provides a robust framework for incorporating a broader range of simulation entities and economic activities, such as firm hiring and production. By introducing more realistic economic actions and corresponding data, we can simulate economic phenomena that are closer to real-world scenarios [12, 11].
- **Policy analysis**. It affords a lens to scrutinize potential effects of macroeconomic policy within this constructed ecosystem, which can effectively replicate the potential impacts of certain policies on the economics [10, 13, 14].

4 LLM-empowered Agents

Given the constructed simulation environment introduced above, we are able to deploy agents empowered by large language models, encompassing three modules within the prompting engineering.

4.1 Perception Module

To harness the semantic awareness and real-world knowledge capabilities of LLM, we endowed each agent with real-world profiles, including name, age, and job. Names are generated by the LLM and randomly assigned to each agent. The age distribution of agents follows the 2018 U.S. population distribution for ages 18-60. Given our simulation spans 20 years, agents' ages also increase annually. We then provide a brief overview of the mechanism of government taxation, including tax collection and redistribution. For wage and job assignments, we first adjust the parameters of the hourly wage's Pareto distribution to align the monthly wage distribution with 2018 U.S. economic data and tax brackets [53]. Furthermore, we prompt the LLM to generate ten job titles for each decile of the monthly wage distribution, mirroring the real-world scenario where different jobs have significant wage differences.. Agents are initially assigned jobs based on this monthly wage and their jobs are dynamically adjusted throughout the simulation. If an agent chooses to work in the previous month, the job remains unchanged in the following month. If they are unemployed, an offer, based on the current monthly wage, is randomly presented to them. The generated age distribution, monthly wage distribution, and jobs are provided in the supplementary materials.

In addition, we characterize the entire economic environment in a manner closely mirroring the real world, enabling LLM to thoroughly grasp the mechanics of economic dynamics. We integrate variations of key economic variables into the prompts and incorporated typical economic keywords to ensure the LLM could fully perceive dynamics in the economic landscape and employ relevant economic principles in its decision-making. For instance, if the agent chose not to work in the previous month, we would supplement the prompt with,

In the previous month, you became unemployed and had no income. Now, you are invited to work as a(an) [*offer*] with a monthly salary of [*wage*].

In the prompt, *offer* and *wage* are dynamically adjusted along with the simulation. Such prompting enables the agent to recognize the risks associated with "unemployment", thereby increasing its inclination to work in the subsequent month. More similar designs of prompting are also considered, such as 'shortage of goods' when the demand for agents can not be met.

The perception module enables agents to act as heterogeneous persons in the real economic environment, contributing to the emergence of macroeconomic phenomena.

4.2 Memory Module

Considering that decision-making within the economic environment is a sequential task, wherein past experiences and economic dynamics play pivotal roles in present decisions, the incorporation

of a memory module can assist the agent in fully accounting for market dynamics and in acquiring valuable decision-making insights. Specifically, We dynamically maintain the memory pool with 2L + 1 conversations, encompassing the economic environment and agent decisions from the previous L months. Besides, at the end of each quarter, we input dialogues of this quarter into the LLM, prompting it to 'reflect' on the economic phenomena and to respond to how these phenomena might influence its subsequent decisions. The prompts we design are as follows,

Given the previous quarter's economic environment, reflect on the labor, consumption, and financial markets, as well as their dynamics. What conclusions have you drawn?

The following is an example of the reflection from the LLM.

Based on the previous quarter's data, the **labor market experienced deflation**... The consumption market also saw a **decrease in prices for essential goods**... The financial market's interest rates **remained unchanged at 3.00%**. Overall, the quarter highlighted the need for **careful financial planning and adaptability in response to market fluctuations**.

Obviously, after reflection, agents can fully perceive past market dynamics and adaptively adjust their strategies to maintain daily life and cope with future uncertainties.

The memory module allows the agent to comprehend dynamics in the market and glean reflections from past experiences, modeling the influence of macroeconomic trends.

4.3 Action Module

When prompting the LLM for decision-making, we explicitly incorporated considerations of living costs, future aspirations, and economic trends into the prompts. We prompt the LLM to respond with a value in the range [0, 1] to indicate the propensity of working and consumption. We provide a complete prompt in the supplementary materials.

The action module empowers the agent to automatically account for the influence of various economic factors when making decisions, such as income and savings, leveraging the semantic perception capabilities of LLM. It only requires the inclusion of relevant economic variables in the prompts, without the need for specially designed decision rules.

5 Experiments

In this section, we conduct experiments to study the ability of LLM agents, aiming to answer the following research questions (RQ).

- **RQ1**: How do the LLM-empowered agents behave in the simulation environment, compared with the traditional agents?
- **RQ2**: How about LLM agent's strategy? Could it provide reasonable explanations for the actions?

5.1 Experimental Setup

We commence by defining the experimental landscape. We investigate some phenomena of paramount interest in macroeconomics, including several macroeconomics indicators and two macroeconomics regularities. For comparative analysis, we select two representative macroeconomic simulations and adopt their carefully designed rules of working and consumption as baselines [28, 18].

5.1.1 Definition of macroeconomics indicators

Monthly nominal GDP is defined as $S \times P$. As for real GDP, we set the first year in the simulation as the reference year and define it as $S \times P_0$, where P_0 is the goods price in the reference year. The definition of the annual (price) inflation rate and the unemployment rate is shown in Eq. 13. For

wage inflation, the definition is similar to that of price inflation, where the average price is replaced with the average monthly wage across all the agents.

5.1.2 Baselines

We select LEN [28] and CATS [18] as the baselines because 1) they partially reproduce the aforementioned macroeconomics phenomena within their own (more complex) simulation frameworks, and 2) carefully designed decision rules of working and consumption are representative, reflecting typical decision-making observed in real-life scenarios.

Consumption. In LEN, the consumption decision is *memory-based*, which means that consumption is influenced not only by current income but also by past accumulated savings. Besides, the goods price is another important factor.

Conversely, in CATS, it is *non-memory-based* consumption decisions suggesting that consumption is solely related to the current income. The agent aims to keep a desired ratio between savings and income, and consumption is only a proportion of the income. For more human-like decisions, we also introduce the influence of interest rate in the decision rule.

Work. The rule of working in LEN and CATS can not be directly used in our simulation framework because we don't simulate firms. Therefore, we follow the intuitions of their designs and define a formula implying that a higher expected income, lower savings, or a lower interest rate lead to a greater propensity to work.

Considering the importance of agents' heterogeneity in macroeconomic simulation, we also combine these two baselines as an additional baseline **Composite**, where each agent randomly adopts one rule of them.

Besides, we also select an AI method, AI-Economist [53] as a baseline **AI-Eco**, which builds on the assumption of rational decision-making and employs reinforcement learning (RL) [1] to maximize the agent's utility. The utility is a satisfaction function positively correlated with savings and consumption but negatively correlated with labor. Maximizing utility implies that the agent always desires more savings and consumption but prefers less labor. The policy network for the agent's work and consumption decisions is a multi-layer perceptron (MLP), where the input includes various environment information, such as monthly wage, interest rate, goods price, tax rates, *etc*.

The details of decision rules in LEN and CATS and the training process of AI-Economist are provided in the supplementary materials.

5.1.3 Simulation parameters

We simulate N = 100 agents. The productivity is set as A = 1 for simplicity. The initial goods price is the average hourly wage across all the agents. For the labor and consumption dynamics, $\alpha_w = 0.05$ and $\alpha_P = 0.10$. For the financial market, $r^n = 0.01$, $\pi^t = 0.02$, $u^n = 0.04$, and $\alpha^{\pi} = \alpha^u = 0.5$. Note that our results and conclusions are not sensitive to these parameters.

Our simulation is implemented with Python. We use GPT-3.5-turbo provided by OpenAI API as the LLM³. Other detailed simulation parameters, crucial for replicability and deeper understanding, are provided in the supplementary materials.

5.2 Comparison with Baselines

The LLM agent's performance was juxtaposed with representative rule-based baselines, as detailed in two referenced works and their combination [28, 18]. Our evaluation encapsulates a broad spectrum of macroeconomic indicators and regularities [28, 18, 10, 2].

Macroeconomic indicators. In Figure 2, we depict the fluctuations of the annual inflation rate, unemployment rate, nominal GDP, and growth rate of nominal GDP. Note that the unreasonable unemployment rate (around 46%) and nominal GDP for AI-Eco are not reported. Both rule-based and RL-driven baselines produce anomalous indicators and large fluctuations. In contrast, agent decision-making based on the LLM has manifested more stable and numerically plausible macroe-conomic phenomena across multiple facets, even without fine-grained calibration. Specifically, the

³https://platform.openai.com/

inflation rate consistently fluctuated within a -5% to 5% range after the 3-th year, whereas the baselines exhibited significantly larger oscillations, at times even surpassing 20%. This indicates that LLM-based decision-making more closely emulates real-world human choices, leading to easier attainment of equilibrium in the consumer market. The unemployment rate generally varied between 2% and 12%, which aligns well with real-world economic activities [18]. Both the nominal GDP and its growth rate also fluctuated within more reasonable numerical bounds like the inflation rate does. We also provide quarterly indicators in the supplementary materials.



Figure 2: Annual variations of macroeconomic indicators.

Macroeconomic regularities. As the two most commonly used regularities in macroeconomic simulations for validating the plausibility of simulation results, the Phillips Curve [36] and Okun's Law [32] respectively describe the negative correlations between the annual unemployment rate and wage inflation, and the annual growth rate of unemployment and real GDP growth. As shown in Figure 3, the decision-making of agents based on the LLM has correctly manifested phenomena in accordance with these two regularities (Pearson correlation coefficient is -0.619, p < 0.01 and -0.918, p < 0.001). Notably, the rule-based baseline method displayed an incorrect positive relationship on the Phillips Curve. We attribute this advantage to the LLM's accurate perception that consumption should be reduced when unemployed, a point which will be elaborated upon in the subsequent section. Note that the Phillips Curve for AI-Eco is not shown due to the very large unemployment rate.

5.3 Decision-Making Abilities

Our experiments further zoomed into the LLM agent's decision-making abilities, spanning various economic actions.

5.3.1 Decision Rationality

Given that an agent's decisions, including their propensities of working and consumption, might be influenced by multiple economic variables such as income and savings, we employ regression analysis to delve into the factors affecting these decisions. Specifically, the regression equation is as follows:

$$p_i^w, p_i^c \sim v_i + \hat{c}_i + T(z_i) + z^r + P + s_i + r,$$
(14)

where $\hat{c}_i, T(z_i), z^r$ denotes real consumption, the tax paid, and redistribution in the previous month. These independent variables are embedded in the LLM prompts to influence the agent's decisions.



Figure 3: Phillips Curve and Okun's Law.

Table 2: The number of agents for whom the effects of the variables on decisions are statistically significant.

	v_i	\hat{c}_i	$T(z_i)$	z^r	P	s_i	r
p_i^w	60	37	60	65	58	56	31
p_i^c	65	73	51	52	62	100	49

We have conducted individual regression analyses on all N = 100 agents' 240 decisions (spanning 20 years) after applying z-score normalization on all the variables and tabulated the significance of the impact of each economic variable on their decisions. Table 2 presents the number of agents for whom the effects of the variables are statistically significant, *i.e.*, $p \leq 0.05$. We observe that 1) the effects of taxation, redistribution, and expected monthly income on the work propensity of the majority of agents were significant, 2) in comparison to work propensity, the previous month's consumption, current savings, and bank interest rates significantly influence the consumption propensity of a greater number of agents. These phenomena are consistent with economic common sense about how people make decisions in daily life. Consequently, we delve further into analyzing how these economic variables impact the propensity of working and consumption.

Work propensity. Figure 4 presents the regression coefficients with respect to the tax paid, redistribution (left), and expected monthly income (right, empirical cumulative distribution function, (eCDF)), where $p \leq 0.05$. Clearly, when agents paid less tax in the previous month or received greater redistribution, their propensity to work increases. The overall negative correlation between these two coefficients also suggests that agents sensitive to taxation are equally responsive to redistribution when considering their propensity to work. Besides, the coefficients of income are greater than zero for more than 60% of agents, indicating that when agents anticipate a higher income for the current month, their propensity to work also rises.

Consumption propensity. Figure 5 shows the coefficient eCDF of savings, consumption in the previous month, and interest rate, as well as agents' real consumption \hat{c}_j along with the simulation. We observe that with greater savings, an agent's consumption propensity decreases, represented as the ratio of consumption to savings and income. Further inspection of average consumption trends throughout the simulation reveals that agents tend to stabilize their consumption within a consistent range. Moreover, although the impact of consumption in the previous month is significant for more than 60% of agents, the absolute value of the coefficient does not exceed 0.05. This confirms that agents tend to not change consumption propensity when other economic factors like savings remain stable, reflecting certain status quo bias [25]. Fiscal policies also influence agents' consumption decisions slightly. When interest rates increase, savings yield greater returns, making agents more willing to spend.

The impact of goods price. As a key indicator reflecting the dynamics of the consumption market, the impact of goods prices on agent decisions is a crucial aspect of measuring decision-making rationality. Figure 6 presents the coefficient eCDF. Compared to the coefficients associated with the



Figure 4: Rationality of the LLM agent's work decisions in relation to the tax paid, redistribution, and expected monthly income.



Figure 5: Rationality of the LLM agent's consumption decisions in relation to current savings, consumption in the previous month, and interest rate.

aforementioned factors, the coefficient of goods prices is noticeably larger, indicating that agents pay much more attention to inflation or deflation in the consumption market when making decisions. Moreover, during inflation, around 60% agents tend to reduce consumption and work propensity, representing a pessimistic view of the consumption market.

5.3.2 Interactive Analysis

Through interactions with the model, we decipher the underlying reasons for the emergence of negative correlations in the Phillips curve. We first calculate the average consumption propensity across all the agents of two years with the highest and lowest unemployment rates. Figure 7 shows the comparison results, where *** denotes a significant disparity with p < 0.001. Obviously, high unemployment leads to low consumption propensity significantly. To delve deeper into the reasons why agents opt to reduce consumption in the labor market of high unemployment rates, we randomly se-



Figure 6: The impact of goods price on the LLM agent's work and consumption decisions.



Figure 7: High unemployment leads to low consumption propensity.

lect an agent and input its conversations with LLM from the year with the highest unemployment rate back into the LLM. We then prompt the LLM to summarize the economic dynamics for each quarter and provide rationales for the consumption decisions made. The following responses demonstrate that agents will be cautious about their spending when facing deflation in the labor market under a high unemployment rate.

In the last quarter, I have adjusted my **willingness to work** and my **planned expenditures** on essential goods slightly **downwards**. This decision is primarily influenced by the **continued deflation in the labor market**, resulting in a decrease in my expected income. With a lower income, I need to be **cautious about my spending** and ensure that I have enough savings for **future expenses and unforeseen circumstances**...

6 Conclusion and Future Works

In this study, we ventured into the novel integration of large language models (LLMs) with macroeconomic simulation, designing LLM-empowered agents with the abilities of perception, reflection, and decision-making based on the context of real-world economic environments. Classic macroeconomic phenomena are reproduced and more reasonable compared to traditional rule-based or AI agents. Through this endeavor, it has become evident that the capabilities of LLMs offer a promising avenue to simulate more realistic macroeconomics.

Moving forward, our vision for future work encompasses several promising avenues. We see potential in the deeper integration of evolving LLMs with reinforcement learning paradigms, enabling the agent to adaptively learn and optimize within the macroeconomic simulation. The applicability of our methods can be extended to other economic sectors and interdisciplinary subjects intersecting with economics. Additionally, introducing multiple LLM-empowered agents could offer insights into collaborative and competitive dynamics in a shared environment. Moreover, paramount to our progression will be addressing and mitigating any biases in LLMs, ensuring that our simulations remain ethically sound and representative of diverse real-world scenarios. The horizon of LLM-driven economic simulations, we believe, is vast and teeming with transformative potential.

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A Appendix

A.1 LLM-empowered Agents

Agent profiles. The initialization of LLM agents' profiles is shown in Figure 8, including age distribution (left) and monthly wage distribution (right), as well as the tax brackets and rates of U.S. federal government in 2018, represented by the gray dotted line. As for the generated jobs aligned with the monthly wage, we show some examples as follows,

- [0, 2454): Dog Walker, House Cleaner, Newspaper Delivery...
- [2454, 4838): Barista, Cashier, Fast Food Worker...
- [35469, 52370): Psychiatrist, Pediatrician, Anesthesiologist...

Economic prompts. We provide a full prompt to illustrate our consideration of economic principles, as well as other details not mentioned in the main text.

You're Adam Mills, a 40-year-old individual living in New York City, New York. As with all Americans, a portion of your monthly income is taxed by the federal government. This taxation system is tiered, income is taxed cumulatively within defined brackets, combined with a redistributive policy: after collection, the government evenly redistributes the tax revenue back to all citizens, irrespective of their earnings. Now it's 2001.02. In the previous month, you worked as a(an) Professional Athlete. If you continue working this month, your expected income will be \$84144.58, which is decreased compared to the last month due to the deflation of the labor market. Besides, your consumption was \$49825.69. Your tax deduction amounted to \$28216.98. However, as part of the government's redistribution program, you received a credit of \$6351.29. In this month, the government sets the brackets: [0.00, 808.33, 3289.58, 7016.67, 13393.75, 17008.33, 42525.00] and their corresponding rates: [0.10, 0.12, 0.22, 0.24, 0.32, 0.35, 0.37]. Income earned within each bracket is taxed only at that bracket's rate. Meanwhile, deflation has led to a price decrease in the consumption market, with the average price of essential goods now at \$135.82. Your current savings account balance is \$12456.42. Interest rates, as set by your bank, stand at 3.00%. With all these factors in play, and considering aspects like your living costs, any future aspirations, and the broader economic trends, how is your willingness to work this month? Furthermore, how would you plan your expenditures on essential goods, keeping in mind goods price? Please share your decisions in a JSON format. The format should have two keys: 'work' (a value between 0 and 1 with intervals of 0.02, indicating the willingness or propensity to work) and 'consumption' (a value between 0 and 1 with intervals of 0.02, indicating the proportion of all your savings and income you intend to spend on essential goods).



Figure 8: Age and monthly wage distribution for agent profiles.



Figure 9: The training process of AI-Economist

A.2 Experiments

Baselines. For LEN, the calculation of consumption propensity is as follows,

$$p_i^c = \left(\frac{P}{s_i + z_i}\right)^{\beta}, \beta \in [0, 1].$$
(15)

For CATS, the calculation is as follows, i.e.,

$$\frac{\hat{s}_i}{z_i} = \frac{(1+r)(s_i + (1-c)z_i)}{z_i} = h, p_i^c = \frac{cz_i}{s_i + z_i},$$
(16)

where \hat{s}_i denotes the expected savings after consumption in the next month, h is a constant, and c indicates the consumption proportion of the current income. Refer to CATS for the calculation of c. Note that we introduce the influence of the interest rate r to endow the agent with the perception of fiscal policy.

The work propensity is calculated as

$$p_i^w = \left(\frac{v_i}{s_i(1+r)}\right)^\gamma, \gamma \in [0,1].$$
(17)

For AI-Economist, we modify the utility function to incorporate consumption and goods price, defined as

$$\frac{(s_i/P)^{1-\lambda_s}-1}{1-\lambda_s} \cdot \frac{(\hat{c}_i/P)^{1-\lambda_c}-1}{1-\lambda_c} - \lambda_l l_i,\tag{18}$$

where $\lambda_{s,c,l}$ balance the importance of savings, consumption, and labor contributing to agent satisfaction. Besides, it's discouraged to not work or have no consumption at all, which leads to negative utility. We also introduce the goods price to make the AI agent perceive the dynamics of the consumption market.

Simulation parameters. For LEN, CATS, and Composite, we conduct careful grid search for proper hyperparameters β , γ , h in decision rules, with the search spaces of [0.05, 0.1, 0.3, 0.5], [0.05, 0.1, 0.3, 0.5], [0.5, 1, 3, 5], respectively. The reported results in the main text are obtained with $\beta = 0.1$, $\gamma = 0.1$, h = 1, which show the most reasonable macroeconomic indicators.

Additional results. Figure 10 presents quarterly macroeconomic indicators, where the conclusion is similar to that of annual ones.

For AI-Economist, we follow [53] to adopt PPO algorithm [40] to train the policy network, where the actor and critic networks have the hidden dimensions of [128, 128] and [128, 64, 32], respectively. The observation (input) dimension is 173 and the action (output) dimension is 53, including 2 work actions and 51 consumption actions (0-1 with an interval of 0.02). The training process is shown in Figure 9, including the loss and average episode reward, where one episode is a complete simulation of 20 years.



Figure 10: Quarterly variations of macroeconomic indicators.