

# Scaling Multi-Agent Systems with Prospect-State Propagation

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## Abstract

Current LLM-based multi-agent systems (MAS) periodically compress intermediate states to reduce inference-time token consumption, thereby attempting to incorporate more agents. However, naive scaling strategies face challenges. For example, in economic simulations, large-scale MAS typically discard semantically rich economic states, *i.e.*, agent behavioral trajectories, which are key drivers of macroeconomic fluctuations. In this paper, we reveal a phenomenon in which agent heterogeneity gradually decreases during simulation, and propose **Prospect-State Propagation for Multi-Agent Systems (PspMAS)**. Inspired by prospect theory, PspMAS decouples each agent’s micro state into a compact Prospect State and an expressive Semantic State. The former records psychological traces through a lightweight, parallelizable propagator and continuously injects heterogeneity into the system. The latter leverages the strong perception, reasoning, planning, and decision-making abilities of LLMs. These two components work complementarily, providing a scalable LLM-based multi-agent simulation solution.

## 1 Introduction

*Humans evaluate potential gains and losses relative to a specific reference point rather than focusing on absolute wealth, ..., is Prospect Theory.*  
– Daniel and Amos (1979)

From Adam Smith’s “invisible hand” in the 18th century to the *behavioral economics* revolution of the 20th century, the study of Macroeconomics has increasingly highlighted the importance of modeling the complexity of human behavior. Traditional representative-agent models (Kirman, 1992; Blanchard, 2017; Christiano et al., 2005) largely circumvent this difficulty by assuming a “perfect world” populated by a single average consumer

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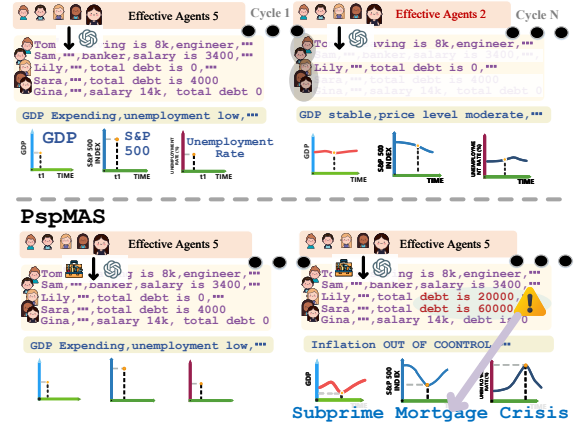


Figure 1: The top sub-figure shows a traditional multi-agent simulation system. After a long-horizon simulation, at cycle  $N$ , the heterogeneity of agents decreases, and the macroeconomic fluctuations are consequently weakened. The bottom sub-figure shows PspMAS. By preserving heterogeneity, the sharp increase in personal mortgage debt for some agents dominates the description of their micro states, thereby facilitating the emergence of macroeconomic phenomena (e.g., the subprime mortgage crisis).

or firm. Such assumptions, however, eliminate distributional heterogeneity and the non-linear aggregate fluctuations (Gabaix, 2011) it generates, limiting the ability to replicate typical macroeconomic events (e.g., crises and recessions).

Agent-based modeling (ABM) offers a bottom-up solution (Farmer and Foley, 2009; Tesfatsion and Judd, 2006). By simulating the behaviors and interactions of heterogeneous agents, ABM allows stylized facts (e.g., GDP, inflation) to emerge from the micro level. Rule-based ABMs maintain a large number of agents with their economic microstate (e.g., income, savings, debt, employment status, wage) that are updated via hand-crafted functions, one representative microstate in the form of key-value pair is `agent:1, income:3200, saving:9000, unemployment status:0, ...`. Such micro states can be batched, parallelized, and vectorized, enabling hardware-efficient simulation.

However, the pre-defined rules fail to capture real psychological processes, ultimately hindering the replication of key macroeconomic dynamics driven by complex human cognition.

Large language models (LLMs) have recently shown remarkable capabilities in natural language understanding (OpenAI, 2023; Liang et al., 2022; Zheng et al., 2023), role-playing (Wang et al., 2024), and contextual reasoning (Yao et al., 2023; Zhu et al., 2024; Dalal et al., 2024), making them attractive for social simulation (Horton, 2023; Argyle et al., 2023; Li et al., 2024b; Xie et al., 2024; Binz et al., 2025; Wang et al., 2024; Zou et al., 2025; Li et al., 2023). The microstate of an LLM-based agent is no longer a fixed set of numbers but a rich semantic description, for example:  ‘You’re Tom, an engineer aged 25. Your saving is 8000, your salary is 3200, and total debt is 0, ..., CPI indicates current economy is in a high-inflation cycle. What level of expenditure do you plan for next period?’ Such semantic-rich microstates enable sufficient behavioural heterogeneity, which is a key driver of macroeconomic fluctuations. But long descriptive profiles of agents during long-horizon simulation consume substantial inference-time token budgets, hindering scalability to large agent populations. Existing multi-agent systems resort to periodic reflection (Park et al., 2023; Shinn et al., 2023), compressing economic histories into high-level summaries. While effective in multi-turn conversations (Qian et al., 2024; Yang et al., 2024; Wu et al., 2024a; Wang et al., 2023b) or code generation tasks, such semantic compression strategies discard the temporal order and intermediate states that are essential for economic decision-making. From the perspective of behavioral economics, human behavior is highly sensitive to early economic fluctuations, and even small changes can exert lasting influences on subsequent choices. Repeated summarization across simulation cycles tends to decrease the dynamic heterogeneity of agents, leading to behavioral homogenization—a phenomenon called *action convergence*. As illustrated in the top part of Fig. 1, a traditional system injects rich descriptions into all agents at system initialization, thereby creating a large nominal population of heterogeneous agents. However, as the simulation proceeds, the micro states of agents are compressed into high-level summaries on a recurring basis. This process gradually removes individual behavioral differences and greatly reduces diversity

among agents. Consequently, macroeconomic fluctuations that should emerge from heterogeneous local distress become attenuated. In macroeconomics, risk signals with genuine predictive value often first appear in the local states of a small subset of agents. If state descriptions are dominated by lagging macro variables such as the unemployment rate, these localized abnormalities can be diluted or erased during semantic compression. As a result, most agents are guided toward a homogenized common context in which the economy still appears broadly healthy, suppressing the micro-to-macro propagation through which crises emerge. For example, in the buildup to the subprime mortgage crisis, early risks were not immediately reflected in aggregate labor-market indicators. Instead, stress first accumulated in agents with average wages but high debt burdens, such as agent Sara  shown in the bottom part of Fig. 1. Such agents can transmit early default risk and other key local signals that eventually develop into the subprime mortgage crisis. If these loan-related micro states are compressed away, the system loses the heterogeneous mechanisms through which localized distress propagates into broader macroeconomic fluctuations.

Based on the above observations, we propose **Prospect-State Propagation for Multi-Agent Systems (PspMAS)**. PspMAS decouples each agent’s micro state into two complementary parts: a compact *Prospect State* and an expressive *Semantic State*. The design of *Prospect State* is inspired by prospect theory, a classical theory in behavioral economics for characterizing human decision-making under gains, losses, and uncertainty. It maintains key psychological variables, including reference point, loss aversion, and probability weighting, and updates them through a fast propagator. *Prospect State* provides the long-term micro-level heterogeneity necessary for economic emergence. *Semantic State* leverages the perception, reasoning, planning, and decision-making abilities of LLMs to generate human-like actions. By combining these two states, PspMAS avoids relying on long textual state descriptions, making the system easier to scale, while also mitigating the heterogeneity loss caused by long-horizon semantic compression. Our contributions are summarized as follows:

- We reveal an inherent heterogeneity-loss problem in MAS for economic simulation, where periodic semantic compression gradually reduces the effective number of behaviorally distinct agents.

- We incorporate prospect theory, preserving long-term heterogeneity.
- We introduce a scalable LLM-based multi-agent simulation solution.

## 2 Method

This section introduces PspMAS, a framework for preserving agent heterogeneity while scaling LLM-based multi-agent systems over long-horizon simulation. The key idea is to decouple each agent’s micro state into two complementary parts: a Markovian Prospect State updated by a lightweight Prospect-State Propagator, and a Semantic State updated periodically by an LLM. We first provide background on multi-agent systems for macroeconomic simulation (Section 2.1), then introduce the simulation loop, including economic state construction, prospect-state propagation, economic state read, and system scaling. Implementation details are given in Section 2.3.

### 2.1 Preliminary

In a Multi-agent Systems (MAS) (Li et al., 2024b; Feng et al., 2025), agents perceive the environment and take actions to achieve goals; their behavior is not hard-coded but emerges from situated interactions with other agents and the environment. We consider a MAS for macroeconomic simulation populated by  $N$  heterogeneous agents, indexed by  $\mathcal{I} = \{1, 2, \dots, N\}$ . The corresponding agent set is  $\{A_i\}_{i \in \mathcal{I}}$ . Each agent is equipped with LLM-powered perception, reasoning, planning, and decision-making abilities. During simulation, agents interact, collectively constructing a macroeconomy, which in turn updates their perceptions and influences subsequent actions.

### 2.2 PspMAS

**Economic State Construction.** Micro differences of agents are a key driver of macroeconomic fluctuations. The combination of agents’ micro states and the environment’s macro state constitutes the Economic State of the simulation.

*Micro State.* Each agent  $A_i$  at time  $t$  maintains an independent micro state capturing its internal behavioral state and economic history. In traditional rule-based ABMs, the micro state is a fixed-dimensional structured vector (Kuroki et al., 2025). In LLM-based simulations, the micro state typically comprises a compact numerical component and a rich semantic component (Li et al., 2024b).

In PspMAS, we write the micro state as

$$\mathcal{M}_i^t = (s_i^t, \sigma_i^t, e_i^t), \quad (1)$$

where  $s_i^t \in \mathcal{P}$  is the Prospect State,  $\sigma_i^t \in \mathcal{M}_{\text{sem}}$  is the Semantic State, and  $e_i^t$  denotes economic bookkeeping variables (e.g., wealth, debt, tax paid, wage, realized consumption, employment status) that are updated by the environment via market clearing. In Particular, the two central branches of PspMAS are  $s_i^t$  and  $\sigma_i^t$ : the former preserves compact psychological traces, while the latter supports expressive natural-language reasoning.

*Macro State.* The overall condition of the economic environment at time  $t$  is described by a macro state  $\mathcal{S}^t$ , typically including price level  $P^t$ , interest rate  $r^t$ , unemployment rate  $u_{\text{emp}}^t$ , and total GDP  $Y^t$ . Formally,  $\mathcal{S}^t \in \mathcal{Y}$ . The macro state reflects the aggregation of all agents’ actions through market mechanisms, forming a closed feedback loop (Li et al., 2024b; Yang et al., 2025).

*Agent Action.* At each time step  $t$ , each agent  $A_i$  selects an action  $a_i^t$  from its action space  $\mathbb{A}_i$  based on its current micro state  $\mathcal{M}_i^t$  and the macro state  $\mathcal{S}^t$ . Following macroeconomic simulation literature, the action space includes two fundamental decisions: whether to work ( $l_i^t \in \{0, 1\}$ ) and what fraction of available funds to spend on consumption ( $p_i^t \in [0, 1]$ ) (Li et al., 2024b; Feng et al., 2025). The action space can be expressed as

$$a_i^t = (l_i^t, p_i^t) \in \mathbb{A}_i = \{0, 1\} \times [0, 1]. \quad (2)$$

**Prospect-State Propagation.** We incorporate prospect theory (Kahneman and Tversky, 2013) into the micro state to capture bounded rationality in decision-making. The theory highlights three key features: - *Reference dependence*: decisions are made based on gains and losses relative to a psychological reference point (e.g., initial wealth), rather than absolute wealth. - *Loss aversion*: losses are felt approximately twice as strongly as equivalent gains (i.e.,  $\lambda \approx 2.25$ ). - *Probability weighting*: people tend to overweight small probabilities and underweight moderate to high probabilities, leading to distorted subjective probabilities.

Based on these insights, we define the Prospect State of agent  $i$  at time  $t$  as a Prospect-State Vector:

$$s_i^t = (\lambda_i^t, \gamma_i^t, R_i^t) \in \mathcal{P} \subset \mathbb{R}^3. \quad (3)$$

Here  $R_i^t$  is the dynamic reference point,  $\lambda_i^t$  the loss-aversion coefficient, and  $\gamma_i^t$  the probability-weighting parameter. Other economic quantities,

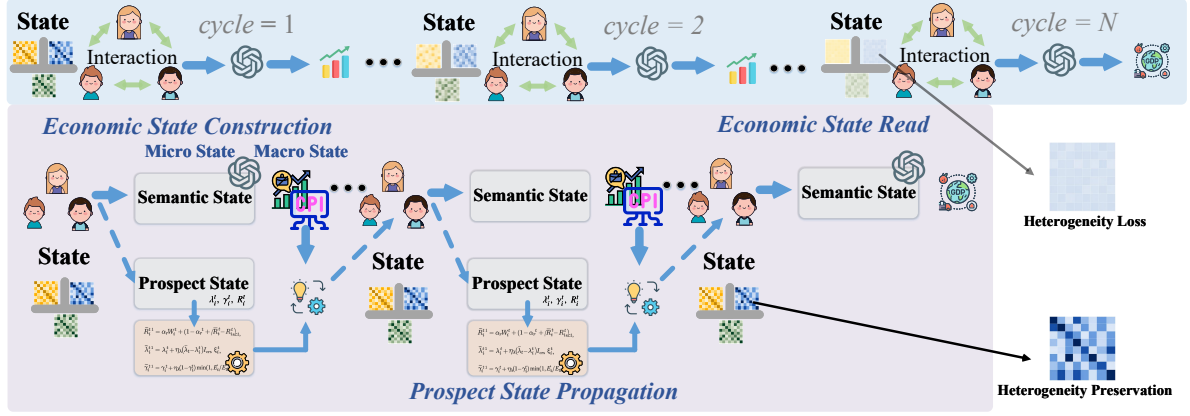


Figure 2: Overview of the major components of PspMAS. PspMAS decouples each agent’s micro state into two complementary branches: a compact Prospect State and an expressive Semantic State. The Prospect State is continuously updated by a lightweight Prospect-State Propagator, preserving psychological traces and injecting long-term heterogeneity into the agent population. The Semantic State is periodically refreshed by the LLM to support perception, reasoning, planning, and human-like decision-making. PspMAS preserves heterogeneous micro dynamics while enabling scalable long-horizon macroeconomic simulation.

such as wealth, income, realized consumption, and unmet demand, are stored as accounting variables or immediate outcomes rather than as dimensions of the Prospect-State Vector.

Let  $o_i^t$  denote the immediate individual outcome produced by market clearing at time  $t$  (e.g., realized labor income, realized consumption, savings change, and unmet demand), and let  $\mathcal{S}^{t+1}$  denote the realized macro state after clearing. The Prospect State update is Markovian:

$$\tilde{s}_i^{t+1} = \Phi(s_i^t, o_i^t, \mathcal{S}^{t+1}), \quad s_i^{t+1} = \Pi_{\mathcal{P}}(\tilde{s}_i^{t+1}), \quad (4)$$

where  $\Pi_{\mathcal{P}}$  projects the updated Prospect-State Vector onto a predefined valid domain  $\mathcal{P}$ . This projection step, rather than the coefficient ranges alone, keeps the Prospect State bounded throughout long-horizon simulation.

The Markovian Prospect-State Propagator  $\Phi$  consists of deterministic, parallelizable lightweight rules:

$$\begin{aligned} \tilde{R}_i^{t+1} &= \alpha_r W_i^t + (1 - \alpha_r) R_i^t + \beta_r (\bar{R}_i^c - R_i^t) I_{\text{scl}}^t, \\ \tilde{\lambda}_i^{t+1} &= \lambda_i^t + \eta_{\lambda} (\bar{\lambda}_t - \lambda_i^t) I_{\text{crs}}^t + \xi_i^t, \\ \tilde{\gamma}_i^{t+1} &= \gamma_i^t + \eta_{\gamma} (1 - \gamma_i^t) \min(1, E_i^t / E_{\text{thr}}) - \zeta I_{\text{shk}}^t, \end{aligned} \quad (5)$$

where  $W_i^t$  is total wealth,  $\bar{R}_i^c$  the cohort-average reference point, and  $I_{\text{scl}}^t$ ,  $I_{\text{crs}}^t$ , and  $I_{\text{shk}}^t$  are indicator flags for social comparison, crisis, and shock, respectively. The variable  $E_i^t$  denotes a recent experience intensity derived from the immediate outcome  $o_i^t$ , and  $E_{\text{thr}}$  is a normalization threshold. After computing Eq. 5, the projection in Eq. 4 is

then applied component-wise to obtain the next Prospect-State Vector, which is denoted by  $s_i^{t+1}$ .

The Semantic State  $\sigma_i^t$  is a textual summary of recent events and agent reflections, updated *periodically* (every  $K$  steps) by an LLM. The LLM receives the current Prospect State  $s_i^t$ , the current accounting variables  $e_i^t$ , a short history of the most recent  $K$  raw events, and the previous Semantic State  $\sigma_i^{t-K}$ , then produces a new  $\sigma_i^t$ . This branch provides perception, reasoning, and human-like decision-making. The two branches operate in parallel: the Prospect State evolves continuously at low cost, preserving long-term path dependence; the Semantic State is refreshed on a longer timescale, injecting rich behavioral patterns without prohibitive token costs.

**Economic State Read.** After all agents have taken their actions, the environment updates the Economic State via a *market clearing function*  $\Psi$ :

$$(\mathbf{M}^{t+1}, \mathcal{S}^{t+1}, \mathbf{o}^t) = \Psi(\mathbf{a}^t, \mathbf{M}^t, \mathcal{S}^t), \quad (6)$$

where  $\mathbf{M}^t = (\mathcal{M}_i^t)_{i \in \mathcal{I}}$ ,  $\mathbf{a}^t = (a_i^t)_{i \in \mathcal{I}}$ , and  $\mathbf{o}^t = (o_i^t)_{i \in \mathcal{I}}$  contains the individual realized outcomes used by the Prospect-State Propagator. In our implementation,  $\Psi$  aggregates intended consumption and labor supply. If total intended demand exceeds total production, goods are rationed proportionally; individual unmet demand  $q_i^t$  is recorded as part of  $o_i^t$  and can affect the next Prospect State update through the experience intensity  $E_i^t$ . Prices and wages adjust according to the imbalance (e.g., demand > supply  $\rightarrow$  price increase). The government collects progressive taxes and redistributes

all revenue equally. Annually, the central bank sets the interest rate using a Taylor rule, and savings earn that interest. This transition closes the loop, feeding macro conditions back into agents' future states, thus cycling repeatedly.

**System Scaling.** PspMAS is designed to scale efficiently to large agent populations while preserving behavioral diversity.

*Computational Scalability.* The Prospect State is updated through lightweight and highly parallelizable propagation rules, avoiding expensive long-context reasoning during most simulation steps. Meanwhile, the Semantic State is refreshed only periodically rather than continuously, substantially reducing the number of costly LLM inference calls while keeping prompts compact over long simulation horizons. Since both state-update branches operate independently across agents, the overall system scales efficiently with the number of agents and simulation steps, enabling large-scale macroeconomic simulations with thousands of agents under practical computational budgets.

*Heterogeneity Quantification.* To measure whether diversity is maintained at scale, we construct three population-level matrices: a Trajectory Matrix, a Prospect Matrix, and a fused Heterogeneity Matrix. The Trajectory Matrix captures realized behavioral diversity from recent action sequences, while the Prospect Matrix captures latent path-dependent psychological diversity from Prospect-State Vectors. The fused matrix combines both views and is used to compute the effective number of distinct behavioral modes.

 *Trajectory Matrix.* Let

$$\mathbf{z}_i^t = (p_i^{t-L+1}, l_i^{t-L+1}, \dots, p_i^t, l_i^t) \quad (7)$$

be the action sequence of agent  $i$  over the last  $L$  steps ( $L = 12$ ). After normalizing  $\mathbf{z}_i^t$  over agents, we construct the Trajectory Matrix as an RBF similarity kernel:

$$H_{\text{traj},ij}^t = \exp\left(-\frac{\|\hat{\mathbf{z}}_i^t - \hat{\mathbf{z}}_j^t\|_2^2}{2\tau_{\text{traj}}^2}\right), \quad (8)$$

where  $\hat{\mathbf{z}}_i^t$  is the normalized trajectory feature and  $\tau_{\text{traj}}$  is a bandwidth parameter. This matrix is large when two agents have similar recent labor and consumption trajectories.

 *Prospect Matrix.* The Prospect Matrix is constructed from the Prospect-State Vector

$$\mathbf{s}_i^t = (\lambda_i^t, \gamma_i^t, R_i^t). \quad (9)$$

After normalizing  $\mathbf{s}_i^t$  over agents, we define

$$H_{\text{pros},ij}^t = \exp\left(-\frac{\|\hat{\mathbf{s}}_i^t - \hat{\mathbf{s}}_j^t\|_2^2}{2\tau_{\text{pros}}^2}\right), \quad (10)$$

where  $\hat{\mathbf{s}}_i^t$  is the normalized Prospect-State feature and  $\tau_{\text{pros}}$  is a bandwidth parameter. This matrix captures whether two agents have similar path-dependent psychological states, even when their recent actions appear similar.

 *Fused Heterogeneity Matrix.* We combine the two matrices with a balance coefficient  $\alpha \in [0, 1]$ :

$$H_{\text{fuse}}^t = \alpha H_{\text{traj}}^t + (1 - \alpha) H_{\text{pros}}^t. \quad (11)$$

Because both  $H_{\text{traj}}^t$  and  $H_{\text{pros}}^t$  are RBF kernels, the fused matrix is positive semidefinite. Therefore, its spectrum can be used as a stable diversity measure.

Let  $\mu_1^t, \mu_2^t, \dots, \mu_N^t$  be the eigenvalues of  $H_{\text{fuse}}^t$ , and normalize them as

$$\tilde{\mu}_k^t = \frac{\mu_k^t}{\sum_{j=1}^N \mu_j^t}. \quad (12)$$

We define the spectral entropy as

$$\mathcal{E}^t = -\sum_{k=1}^N \tilde{\mu}_k^t \log(\tilde{\mu}_k^t + \epsilon), \quad (13)$$

and the effective diversity as

$$\mathcal{D}_{\text{eff}}^t = \exp(\mathcal{E}^t). \quad (14)$$

The normalized diversity is

$$D_{\text{norm}}^t = \frac{\mathcal{D}_{\text{eff}}^t}{N}. \quad (15)$$

When agents collapse into highly similar behaviors and similar Prospect States,  $H_{\text{fuse}}^t$  approaches a low-rank matrix and  $\mathcal{D}_{\text{eff}}^t$  becomes correspondingly small. When agents remain behaviorally and psychologically diverse, the effective diversity remains high. These metrics are computed periodically and used to assess heterogeneity preservation over long-horizon simulation.

**Long-Horizon Simulation Loop.** The simulation proceeds over a finite horizon  $T$ . The full simulation trajectory is

$$\tau = (\mathbf{M}^0, \mathcal{S}^0, \mathbf{a}^0, \mathbf{M}^1, \mathcal{S}^1, \dots, \mathbf{M}^T, \mathcal{S}^T). \quad (16)$$

Algorithm 1 summarizes the entire simulation loop. At each time step, for each agent we optionally update the Semantic State every  $K$  steps,

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**Algorithm 1** Prospect-State Propagation Simulation Loop
 

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1: Input:  $N$  agents, horizon  $T$ , update interval  $K$ , initial macro state  $\mathcal{S}^0$ 
2: Initialize micro states  $\{\mathcal{M}_i^0\}_{i=1}^N$  with profiles (basic, economic, psychological)
3: for  $t = 0$  to  $T - 1$  do
4:   for each agent  $i$  in parallel do
5:     if  $t \bmod K = 0$  then
6:       Update Semantic State  $\sigma_i^t \leftarrow \text{LLM}(s_i^t, e_i^t, \text{history}_{t-K+1:t}, \sigma_i^{t-K})$ 
7:     end if
8:     Generate economic action  $a_i^t \sim \pi_\theta(\cdot | s_i^t, \sigma_i^t, e_i^t, \mathcal{S}^t)$ 
9:   end for
10:  Execute market clearing  $\Psi$ : compute  $\mathcal{S}^{t+1}$  and record outcomes  $\{o_i^t\}_{i=1}^N$ 
11:  for each agent  $i$  in parallel do
12:    Update Prospect State  $s_i^{t+1} = \Pi_{\mathcal{P}}(\Phi(s_i^t, o_i^t, \mathcal{S}^{t+1}))$ 
13:  end for
14:   Construct  $H_{\text{traj}}^t$ ,   $H_{\text{pros}}^t$ , and   $H_{\text{fuse}}^t$ ; compute  $\mathcal{E}^t$ ,  $\mathcal{D}_{\text{eff}}^t$ , and  $D_{\text{norm}}^t$ 
15: end for

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then call the LLM to generate actions, execute market clearing, and update Prospect States with the Prospect-State Propagator. Heterogeneity is quantified by the spectral entropy  $\mathcal{E}^t$  and effective diversity  $\mathcal{D}_{\text{eff}}^t$  of the fused Heterogeneity Matrix  $H_{\text{fuse}}^t$ , which combines the Trajectory Matrix and the Prospect Matrix.

### 2.3 Implementation Details

Our implementation uses Qwen3-family models (Team, 2025). The temperature is set to 0.7 for decision calls and 0.2 for summarization. The update interval  $K$  is set to 5. The Prospect-State Propagator coefficients are  $\alpha_r = 0.1$ ,  $\beta_r = 0.05$ ,  $\eta_\lambda = 0.001$ ,  $\eta_\gamma = 0.005$ ,  $\zeta = 0.1$ ,  $\sigma_\lambda = 0.02$ . The threshold  $E_{\text{thr}} = 10$ . Unless otherwise specified, each Prospect-State update is projected onto the predefined valid domain  $\mathcal{P}$  after Eq. 5. For heterogeneity evaluation, we set the trajectory window to  $L = 12$  and use  $\alpha = 0.5$  in the fused Heterogeneity Matrix unless otherwise specified. Additional implementation details and parameter sensitivity analyses are reported in the Appendix.

## 3 Experiments

Our experiments answer the following research questions:

**RQ1:** Why does increasing the number of agents fail to produce effective scaling in a state-of-the-art LLM-based economic simulation system?

**RQ2:** Does the proposed Prospect-State Propagation preserve agent heterogeneity at scale?

### 3.1 Experimental Setting

*Simulation Environment.* We simulate a closed economy where each agent makes labor supply and consumption decisions at each step. The macro state includes GDP, inflation, and unemployment.

*Baseline Methods.* We compare four representative multi-agent architectures:

- **SaMAS:** A situation-aware LLM-driven generative system for economic simulation, used as the strong prior system in our direct comparison (Chen and Chen, 2026).
- **SUMMARY SYSTEM:** Agents use plain summary: their histories are periodically compressed into LLM-generated summaries ( $K = 5$ ). The summary replaces raw event history in the context window (Park et al., 2023; Qian et al., 2024).
- **REFLECTION SYSTEM:** Agents use periodic reflection: they maintain a memory stream and generate high-level reflections (“insights”) at regular intervals ( $K = 5$ ). Reflections are stored alongside recent events (Shinn et al., 2023; Wang et al., 2023a).
- **PspMAS:** Agents maintain a compact Prospect-State Vector  $s_i^t \in \mathbb{R}^3$  updated via deterministic propagator at every step; Semantic State refreshed every  $K = 5$  steps.

### 3.2 RQ1: Scaling Analysis of SaMAS and PspMAS

We conduct a scaling analysis of PspMAS and SaMAS (Chen and Chen, 2026) using Qwen3-32B (Team, 2025) under the same evaluation protocol, including the same simulation horizon and comparable token budgets. We report results at two agent scales,  $N = 100$  and  $N = 500$ , using Volatility Realism (VR) and normalized fused diversity  $D_{\text{norm}}$ .

Table 1 exposes a clear failure of the expected scaling law in SaMAS. A fivefold increase in nominal population, from  $N = 100$  to  $N = 500$ , improves VR by only 0.2 points (81.8% to 82.0%), while  $D_{\text{norm}}$  drops by 9.9 points (43.2% to 33.3%). Performance therefore does not improve consistently with scale: the marginal gain in realism nearly vanishes, while the effective population becomes substantially more homogeneous. This result shows that nominal agent count is not equivalent to effective system scale when repeated semantic compression drives behavioral convergence. In contrast, PspMAS increases VR from 82.9% to 85.3% while retaining substantially higher diversity (61.9% at  $N = 100$  and 56.9% at  $N = 500$ ). At  $N = 500$ , it exceeds SaMAS by 3.3 points in VR and 23.6 points in  $D_{\text{norm}}$ . This contrast indicates that preserving state heterogeneity is a prerequisite for realizing the expected benefits of scaling in MAS.

### 3.3 RQ2: Heterogeneity Preservation at Scale

To quantify whether PspMAS preserves agent heterogeneity as the system scales, we compute the normalized diversity  $D_{\text{norm}} = \mathcal{D}_{\text{eff}}/N$  from the fused Heterogeneity Matrix  $H_{\text{fuse}}^t$  defined in Section 2.2. This matrix combines the Trajectory Matrix, which measures recent action diversity, and the Prospect Matrix, which measures path-dependent psychological diversity. Higher  $D_{\text{norm}}$  indicates more behaviorally distinct agents.

**Varying agent count.** Table 2 shows  $D_{\text{norm}}$  as a function of  $N$ . SUMMARY SYSTEM saturates at  $N \approx 200$ , confirming that repeated semantic compression homogenizes both recent action trajectories and prospect-state traces regardless of population size. REFLECTION SYSTEM shows sublinear scaling. In contrast, PspMAS maintains high fused diversity even at  $N = 500$ , demonstrating stronger heterogeneity scaling.

**Varying model size.** Table 3 examines the effect of LLM backbone size on heterogeneity preservation. Scaling from Qwen3-8B to Qwen3-32B increases  $D_{\text{norm}}$  from 32.1% to 36.5% for REFLECTION SYSTEM and from 58.2% to 62.5% for PspMAS.

**Varying simulation horizon.** Table 4 summarizes  $D_{\text{norm}}$  at simulation horizons 50 and 200. SUMMARY SYSTEM degrades rapidly as repeated compression accumulates information

loss. REFLECTION SYSTEM shows more graceful degradation but still suffers from cumulative drift. PspMAS maintains remarkably stable fused diversity, indicating that the Prospect-State Propagator preserves both behavioral trajectories and path-dependent prospect-state differences over long horizons. Complete results for all evaluated horizons are reported in Appendix C.1.

### 3.4 Summary of Findings

**RQ1:** Failure of scaling in SOTA MAS: Increasing the SaMAS population fivefold, from  $N = 100$  to  $N = 500$ , improves VR by only 0.2 points while reducing  $D_{\text{norm}}$  from 43.2% to 33.3%. In contrast, PspMAS improves VR from 82.9% to 85.3% while retaining much higher diversity (61.9% to 56.9%), showing that heterogeneity enables effective scaling.

**RQ2:** Heterogeneity preservation at scale: At  $N = 500$ , PspMAS maintains  $D_{\text{norm}} > 0.56$ , whereas SUMMARY SYSTEM saturates near  $N = 200$  ( $D_{\text{norm}} \approx 0.21$ ). This advantage persists across LLM sizes and simulation horizons.

## 4 Related Work

**Macroeconomic Simulation** Traditional macroeconomic models such as DSGE (Smets and Wouters, 2007; Clarida et al., 1999; Christiano et al., 2005) and VAR (Sims, 1980; Negro et al., 2015) primarily analyze economic fluctuations and policy transmission in a top-down manner through mathematical modeling of the relationship between “representative agents” and macroeconomic variables. Agent-based Modeling adopts a “bottom-up” paradigm for social simulation: by simulating the behaviors and interactions of micro-level individuals within a specific environment, it reproduces macroeconomic phenomena, thereby overcoming the limitation of the “representative agent” assumption inherent in traditional models (Acemoglu et al., 2012; Poledna et al., 2023; Caiani et al., 2016; AxteLL, 2001; Geanakoplos et al., 2012; Dawid and Delli Gatti, 2018). In recent years, LLM-driven agents have endowed ABM with scenario-based interaction capabilities, allowing for the simulation of more complex economic behaviors and enabling more sophisticated economic simulations (Yang et al., 2025; Li et al., 2024b; Chen et al., 2024b; Li et al., 2025a; Taylor and Bergen, 2025; Anthis et al., 2025; Xie et al., 2024; Widler et al., 2026). Despite these advances, existing approaches largely rely

Table 1: Comparisons with the strong baseline SaMAS (Chen and Chen, 2026).

| $N$ | System | VR (%) $\uparrow$ | $D_{\text{norm}}$ (%) |
|-----|--------|-------------------|-----------------------|
| 100 | SaMAS  | 81.8              | 43.2                  |
| 100 | PspMAS | <b>82.9</b>       | <b>61.9</b>           |
| 500 | SaMAS  | 82.0              | 33.3                  |
| 500 | PspMAS | <b>85.3</b>       | <b>56.9</b>           |

Table 3: Normalized fused diversity  $D_{\text{norm}}$  (%) under different LLM sizes.

| Model        | REFLECTION | PspMAS |
|--------------|------------|--------|
| Qwen 3 - 8B  | 32.1       | 58.2   |
| Qwen 3 - 32B | 36.5       | 62.5   |

on periodic semantic summarization or reflection to compress long economic histories, a practice that risks attenuating fine-grained behavioral trajectories. This compression, though token-efficient, tends to homogenize agents over time by progressively smoothing away their early fluctuations.

**LLM-driven Agentic System** AI Agent is an autonomous system that perceives its environment and takes actions to achieve goals. These actions are not hard-coded but rather emerge from situated interactions, continuously evolving through feedback from interactions with the environment and other agents. This paradigm has achieved notable success in multi-turn conversation systems (Zheng et al., 2023; Wu et al., 2024a), code generation (Jimenez et al., 2024; Yang et al., 2024), and general-purpose assistant tasks (Wang et al., 2024; Chen et al., 2024b). Furthermore, the same paradigm has advanced social reasoning (Gandhi et al., 2023; Sap et al., 2019; Mankowitz et al., 2023; Zhang et al., 2024), policy optimization (Silver et al., 2017, 2016), and behavioral simulation (Chen et al., 2024a; Park et al., 2023; Xie et al., 2024; Li et al., 2024a). This paradigm excels at leveraging LLMs for flexible, context-aware reasoning, enabling agents to adapt to novel situations without hand-crafted rules. The feedback-driven, interactive design also allows agents to continuously refine their strategies, producing emergent behaviors that static models cannot replicate. As individual agent capabilities improve, LLM-driven Multi-agent Systems have come into sharper focus, and recent research has begun to further investigate the collective behavior and emergent dynam-

Table 2: Normalized fused diversity  $D_{\text{norm}}$  (%) under varying agent count  $N$ .

| $N$ | SUMMARY | REFLECTION | PspMAS |
|-----|---------|------------|--------|
| 20  | 68.2    | 71.3       | 73.8   |
| 50  | 40.3    | 55.6       | 67.5   |
| 200 | 21.2    | 33.5       | 59.6   |
| 500 | 20.1    | 30.5       | 56.5   |

Table 4: Normalized fused diversity  $D_{\text{norm}}$  (%) under different simulation horizons.

| Horizon | SUMMARY | REFLECTION | PspMAS |
|---------|---------|------------|--------|
| 50      | 28.5    | 42.5       | 61.2   |
| 200     | 18.5    | 30.2       | 57.8   |

ics arising from multi-agent interactions. Recent work demonstrates that LLM-based multi-agent systems can spontaneously form social norms, collaborative structures, and complex group behaviors through ongoing interaction (Li et al., 2025b; Schneider et al., 2025; Wu et al., 2024b; Riedl, 2025). Moreover, recent efforts have leveraged these systems for macroeconomic forecasting (Jin et al., 2024; Ansari et al., 2024; Rasul et al., 2023; Garza et al., 2023), revealing intricate emergent macro-level phenomena.

## 5 Conclusion

We present PspMAS, the first macroeconomic simulation MAS that incorporates prospect theory into economic state updating. To achieve this, we first decouple each agent’s micro state into two complementary components. We then leverage the Prospect State to continuously inject heterogeneity into the system, while using the Semantic State to generate human-like actions. By combining the two, PspMAS not only significantly reduces LLM inference token consumption, making effective scaling possible, but also achieves strong simulation performance. More broadly, our work provides new insights into addressing the challenges of LLM-driven MAS through classic theories from behavioral economics. Future work could extend PspMAS to other complex socio-economic domains such as financial market regulation, climate policy negotiation, and organizational behavior simulation, where bounded rationality and heterogeneous decision-making play critical roles.

## Limitations

This study has several limitations. First, the current simulations are still conducted within a simplified closed economy environment, and thus may fail to capture open economy effects, institutional constraints, or real-world policy frictions. Second, decisions based on large language models may inherit biases from their underlying models; future research should examine robustness across different model families, prompting strategies, and calibration settings. Third, during the training process, large language models absorb cultural, political, and ideological biases from the internet, academic literature, and policy documents. It is currently impossible to completely disentangle these deep-seated value orientations, posing a serious challenge for applications seeking "value-neutral" policy insights in practice.

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## A Broader Impact

Our work introduces PspMAS, a scalable multi-agent simulation framework that preserves agent heterogeneity via prospect-state propagation. On the positive side, PspMAS enables more realistic macroeconomic modeling by maintaining long-term behavioral diversity under fixed token budgets, which can improve the fidelity of policy simulations, stress testing, and economic forecasting. The decoupled architecture—compact Markovian prospect states plus periodic LLM-based semantic updates—provides a general blueprint for scaling LLM-driven agent systems beyond economics, potentially benefiting domains such as urban planning, supply chain management, and epidemiological modeling. Moreover, the spectral diversity metric we introduce offers a principled way to quantify and monitor agent heterogeneity, which can be adopted as a diagnostic tool in any multi-agent simulation.

On the negative side, several risks warrant consideration. First, although PspMAS reduces reliance on long-text compression, the semantic branch still depends on LLMs, which may inherit or amplify biases present in their training data (e.g., stereotypes about income groups or consumption behavior). If the initial agent profiles or economic scenarios are not carefully designed, the simulation could produce systematically skewed macro outcomes that reinforce real-world inequalities. Second, the prospect-state propagator, while lightweight and parallelizable, is based on parameterized rules (e.g., loss-aversion update, reference-point adaptation). Inappropriate parameter settings or unrecognized feedback loops could lead to emergent behaviors that are economically unrealistic or unstable, potentially misleading policymakers if the system is deployed for real-world guidance. Third, as with any agent-based economic simulator, there is a risk of dual use: malicious actors might adapt the framework to model manipulative market strategies or to stress-test financial systems in ways that create systemic vulnerabilities. However, these risks are not unique to PspMAS; they are inherent to any high-fidelity economic simulation tool. We emphasize that our contribution is methodological, and we strongly advocate for transparent reporting of model parameters, initial distributions, and LLM prompts, as well as routine diversity audits using the proposed spectral metrics, to mitigate these concerns without compromising the core innovation.

## B Experimental Settings

**Evaluation Metrics.** Following recent economic simulation literature (Li et al., 2024b; Yang et al., 2025), we evaluate simulation realism using two complementary metrics.

**Volatility Realism (VR).** VR measures the similarity between the statistical properties of simulated macroeconomic variables and those observed in real-world data. Specifically, we compute the Pearson correlation coefficient between each simulated variable (e.g., GDP, inflation, unemployment) and its real-world counterpart. VR is then defined as the average correlation across all macro variables. Higher VR indicates more realistic volatility patterns.

**Turning-Point Hit Rate (HR).** HR quantifies the model’s ability to correctly identify the timing of economic cycle turning points (peaks and troughs). Following common practice, we evaluate HR at three temporal resolutions: daily (HR-d), monthly (HR-m), and yearly (HR-y). For each resolution, a turning point is considered correctly predicted if the simulated turning date falls within a tolerance window of the actual turning date (e.g.,  $\pm 5$  days for daily,  $\pm 1$  month for monthly,  $\pm 2$  months for yearly). The final HR is the ratio of correctly predicted turning points to the total number of real turning points, expressed as a percentage.

## C Additional Experimental Results and Sensitivity Analysis

### C.1 Complete Simulation-Horizon Results

Table 5 reports the complete normalized fused diversity results for all evaluated simulation horizons.

Table 5: Complete normalized fused diversity  $D_{\text{norm}}$  (%) results under varying simulation horizon.

| Horizon | SUMMARY | REFLECTION | PspMAS |
|---------|---------|------------|--------|
| 50      | 28.5    | 42.5       | 61.2   |
| 100     | 23.1    | 36.2       | 60.1   |
| 150     | 20.5    | 32.8       | 58.9   |
| 200     | 18.5    | 30.2       | 57.8   |

### C.2 Parameter Sensitivity Analysis

Unless otherwise stated, all sensitivity experiments use  $N = 200$  agents and Qwen3-8B. We vary one parameter at a time while holding the remaining parameters at their default values, and use one shared

configuration across environments and evaluation metrics rather than tuning separately for each metric.

**Prospect-state propagation parameters.** We first vary the three psychological-state update parameters. The reference-point coefficient  $\alpha_r$  is evaluated with  $\beta_r = 0.05$  fixed; the loss-aversion update rate  $\eta_\lambda$  is evaluated with  $\sigma_\lambda = 0.02$  fixed; and  $\eta_\gamma$  controls the evolution of probability weighting under uncertainty. The default values are  $\alpha_r = 0.10$ ,  $\eta_\lambda = 0.001$ , and  $\eta_\gamma = 0.005$ . Table 6 shows that  $D_{\text{norm}}$  changes smoothly rather than depending on a brittle parameter choice, supporting the balanced default configuration.

Table 6: Sensitivity of PspMAS to prospect-state propagation parameters.

| Parameter                                             | Value  | $D_{\text{norm}}$ (%) $\uparrow$ |
|-------------------------------------------------------|--------|----------------------------------|
| Reference-point sensitivity ( $\beta_r = 0.05$ )      |        |                                  |
| $\alpha_r$                                            | 0.05   | 57.8                             |
| $\alpha_r$                                            | 0.10   | 58.2                             |
| $\alpha_r$                                            | 0.20   | 58.0                             |
| $\alpha_r$                                            | 0.30   | 57.3                             |
| $\alpha_r$                                            | 0.50   | 56.4                             |
| Loss-aversion sensitivity ( $\sigma_\lambda = 0.02$ ) |        |                                  |
| $\eta_\lambda$                                        | 0.0005 | 57.5                             |
| $\eta_\lambda$                                        | 0.001  | 58.2                             |
| $\eta_\lambda$                                        | 0.002  | 58.7                             |
| $\eta_\lambda$                                        | 0.005  | 59.2                             |
| $\eta_\lambda$                                        | 0.010  | 59.8                             |
| Probability-weighting sensitivity                     |        |                                  |
| $\eta_\gamma$                                         | 0.001  | 56.8                             |
| $\eta_\gamma$                                         | 0.003  | 57.7                             |
| $\eta_\gamma$                                         | 0.005  | 58.2                             |
| $\eta_\gamma$                                         | 0.010  | 58.9                             |
| $\eta_\gamma$                                         | 0.020  | 59.5                             |

**Heterogeneity-matrix balance coefficient.** We recompute  $D_{\text{norm}}$  from the same logged trajectories while varying the fusion coefficient  $\alpha$  in Eq. 11. As shown in Table 7, the metric changes smoothly across the full range. We use  $\alpha = 0.5$  because it assigns equal weight to realized behavioral trajectories and latent prospect-state diversity, rather than because it maximizes the reported metric.

**Semantic-state update interval.** Table 8 reports the trade-off induced by varying  $K$ . Updating more frequently slightly improves diversity but substan-

Table 7: Sensitivity of  $D_{\text{norm}}$  (%) to the Heterogeneity Matrix balance coefficient  $\alpha$ .

| $\alpha$ | $D_{\text{norm}}$ (%) $\uparrow$ |
|----------|----------------------------------|
| 0.00     | 59.5                             |
| 0.25     | 58.9                             |
| 0.50     | 58.2                             |
| 0.75     | 57.4                             |
| 1.00     | 56.1                             |

tially increases token usage, whereas large intervals save tokens at the cost of recent-signal preservation. We therefore use  $K = 5$  as a balanced setting between heterogeneity preservation and token efficiency.

Table 8: Sensitivity to the Semantic-State update interval  $K$ . Token usage is measured in millions.

| $K$ | Token usage (M) $\downarrow$ | $D_{\text{norm}}$ (%) $\uparrow$ |
|-----|------------------------------|----------------------------------|
| 1   | 220.0                        | 57.2                             |
| 3   | 171.5                        | 56.9                             |
| 5   | 161.8                        | 56.5                             |
| 10  | 154.5                        | 54.8                             |
| 20  | 150.9                        | 52.6                             |