From Peer Learning to Collective Involution: An Agent-Based Study of Ride-Hailing Drivers' Market Participation

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Abstract. Platform labor markets have increasingly exhibited involutionary competition,particularly among ride-hailing drivers facing uncertain earnings and intense market pressure. Existing studies mainly explain participation decisions through economic incentives, while the role of peer influence remains underexplored. To address this gap, this study develops a utility-threshold agent-based model that integrates utility evaluation, social comparison, and network learning.Simulation results show that collective involution can emerge endogenously through decentralized behavioral adaptation, characterized by rising labor intensity and declining marginal labor returns. Utility thresholds reduce excessive competition, whereas peer influence significantly strengthens involutionary dynamics. Moreover, behavioral convergence has a stronger effect on collective outcomes than imitation sensitivity, suggesting that synchronized adaptation is a key driver of labor competition. In contrast, psychological factors mainly influence the economic consequences of involution rather than its emergence. The findings provide a computational explanation for collective involution in platform labor markets and highlight the importance of social learning in shaping labor participation dynamics.

Keywords: Platform Labor · Ride-Hailing Drivers · Peer Influence · Collective Involution; Agent-Based Modeling.

1 Introduction

The rapid expansion of digital labor platforms has transformed labor market organization, enabling workers to freely determine participation intensity. Ride-hailing services exemplify this flexibility: labor supply adjusts nearly instantaneously to market conditions, with drivers' participation decisions shaped by earnings expectations, platform incentives, and demand fluctuations. Yet this growth has also generated growing concerns about labor involution. When active drivers expand faster than passenger demand, workers frequently extend working hours or remain active despite declining earnings—strategies that fail

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to produce sustained advantages when adopted collectively. Most existing research explains market participation primarily through economic incentives and assumes independent decision-making, leaving the collective mechanisms of involutionary competition insufficiently understood.

A critical limitation is the neglect of peer influence. In practice, drivers are embedded in formal and informal social networks—online communities, messaging groups, and driver associations—through which they compare earnings, exchange strategies, and update expectations. Social learning theory, peer-effect research, and network science suggest that such interactions significantly shape collective behavioral outcomes. However, because social influence is decentralized and difficult to measure directly, existing studies provide limited explanations of how utility perception, social comparison, and peer learning jointly determine participation dynamics in platform markets.

Although substantial progress has been made in platform labor research, social network analysis, and computational behavioral modeling, a coherent explanation of ride-hailing drivers' market participation dynamics is still lacking. Existing studies generally treat market entry and exit as independent responses to economic incentives. Such approaches overlook bounded rationality, adaptive adjustment, and the persistent uncertainty that characterizes platform work. At the same time, ride-hailing drivers are widely embedded in formal and informal social networks. Yet the structure and influence of these networks remain difficult to observe, and their behavioral consequences are not fully understood. From a modeling perspective, threshold models and agent-based simulations have proven effective for studying diffusion and collective behavior. However, they have seldom been used to analyze labor-market participation under social influence. Current models provide limited explanations of how utility perception, peer interactions, and behavioral updating jointly shape market dynamics. To address these limitations, this study develops a utility-threshold agent-based model that integrates labor utility, peer influence, and bounded-rational updating. The model aims to explain how ride-hailing drivers dynamically adjust market participation under uncertain platform labor conditions and how these micro-level adaptations generate collective behavioral patterns.

To address these gaps, this study develops a utility-threshold agent-based model integrating utility evaluation, bounded rationality, and peer influence. Drivers continuously assess labor utility relative to individual participation thresholds while updating behavior through network-based learning and social comparison. By combining utility perception, relative deprivation, and Fermi-based behavioral diffusion within a unified computational framework, the model captures how micro-level adaptations generate macro-level patterns of labor competition. The study contributes three advances: extending platform labor research with a utility-threshold participation mechanism; incorporating peer influence to reveal how social learning amplifies competitive behavior; and demonstrating how agent-based modeling explains collective involution as a complex adaptive phenomenon.

2 Literature Review

2.1 Market Participation and Labor Dynamics in Platform Economies

Digital platforms have fundamentally reshaped labor markets by enabling flexible, on-demand work arrangements in which workers freely determine entry, persistence, and exit, rendering labor supply highly dynamic and responsive to market conditions—a pattern particularly evident in ride-hailing [2, 3].

Existing studies primarily explain driver participation through economic incentives, including surge pricing, platform subsidies, and labor flexibility [1, 3].however, they generally assume independent decision-making driven by individual utility maximization.

Recent research challenges this assumption by emphasizing the precarious nature of platform work. Despite nominal flexibility, workers often face unstable earnings, algorithmic management, and persistent competitive pressure [4, 13].As participation expands, labor supply frequently outpaces demand, intensifying competition and generating involution—wherein workers increase effort merely to maintain income—a dynamic widely observed among ride-hailing drivers, food-delivery couriers, and other gig workers [15].Ride-hailing participation thus constitutes not only an economic choice but also an adaptive process shaped by uncertainty and competition; yet existing research pays limited attention to behavioral adjustment through social interaction, leaving the mechanisms linking individual perception and collective dynamics insufficiently understood.

2.2 Social Networks, Peer Influence, and Behavioral Diffusion

A substantial body of research indicates that behavior is shaped by social interaction, information exchange, and observational learning. Social learning theory posits that individuals update beliefs and expectations by observing others' actions and outcomes [5].while peer-effect research demonstrates that social influence affects decisions across education, labor markets, technology adoption, and consumption [6].

Advances in network science further identify complex networks as the structural basis for the diffusion of information, opinions, and behaviors [7]. Individuals therefore respond not only to objective market conditions but also to information derived from local social environments, making network structure central to behavioral outcomes.

In platform labor markets, such interactions are particularly salient due to incomplete information and high uncertainty. Ride-hailing drivers frequently exchange experiences through online communities and informal networks to interpret market conditions and form earnings expectations, with prior studies confirming that peer influence affects labor participation, work intensity, and strategic decision-making under uncertainty [9, 13].

Building on complex contagion theory, behavioral change often requires reinforcement from multiple contacts rather than exposure to a single individual [8,

10].a mechanism especially relevant for drivers facing economic risk and uncertain outcomes. Nevertheless, empirical evidence on drivers' social networks remains limited, leaving both the extent and mechanisms of peer influence underexplored.

2.3 Threshold-Based Behavioral Modeling in Computational Social Science

Threshold models remain a foundational framework for explaining behavioral change in social systems, premised on the idea that individuals alter behavior only when perceived incentives or social pressures exceed a threshold—a mechanism shown to generate complex collective outcomes including segregation, collective action, and social diffusion [14]

With the rise of computational social science, these models have been integrated with agent-based modeling (ABM), evolutionary dynamics, and network analysis to study macro-level patterns emerging from decentralized interactions among heterogeneous agents [11, 14].Recent advances in large language models (LLMs) and generative agents further enrich cognitive and behavioral representations in simulation, renewing interest in integrating behavioral theory with computational modeling [12].

Despite this progress, threshold-based approaches have rarely been applied to platform labor markets. Existing studies focus predominantly on cooperation, diffusion, and opinion dynamics, with limited attention to labor-market entry and exit, and few models incorporate utility perception, social influence, and behavioral updating within a unified framework. Existing approaches typically treat entry and exit as independent responses to economic incentives, overlooking bounded rationality, adaptive adjustment, and persistent uncertainty; while threshold models and agent-based simulations effectively capture diffusion and collective behavior, they have seldom been applied to labor-market participation under social influence. Consequently, current models offer limited insight into how utility perception, peer interaction, and behavioral updating jointly shape market dynamics. To address these gaps, this study develops a utility-threshold agent-based model integrating labor utility, peer influence, and bounded-rational updating to explain how drivers dynamically adjust participation under uncertain platform conditions and how such micro-level adaptations generate collective behavioral patterns.

3 Conceptual Framework and Model Design

3.1 Adaptive Participation Dynamics in Platform Labor Markets

Traditional labor supply theory models participation as a utility-maximization problem in which individuals allocate working time according to expected earnings and leisure preferences. Formally, an individual chooses the action a_i that maximizes utility:

$$\sigma_i^* = \arg\max U_i(a),$$

where $U_i(a)$ denotes the utility associated with action a. This framework assumes sufficient market information, predictable future returns, and independent decision-making.

However, these assumptions become increasingly problematic in platform-mediated labor markets. Platform work is characterized by four structural features that fundamentally challenge classical assumptions: *algorithmic opacity*,whereby drivers cannot observe order allocation rules; *earnings uncertainty*, as similar labor inputs may yield substantially different outcomes due to demand fluctuations and algorithmic allocation; *localized information*, forcing reliance on peer networks rather than market-wide observation; and *dynamic governance*, where pricing rules and incentive schemes change continuously, rendering any given strategy unstable. Together,these features imply that participation is better understood as an adaptive process than as a static optimization problem.

Accordingly, let $a_i(t)$ denote the behavioral state of driver i at time t. The evolution of behavior is represented as

$$a_i(t+1) = F\big(a_i(t), E_i(t)\big),$$

where $E_i(t)$ is the information available to the driver and $F(\cdot)$ an adaptive updating process. Such adaptation generates feedback at both individual and market levels: past outcomes shape future decisions, while collective adjustments alter competition intensity and earning opportunities, which subsequently influence future behavior. Platform labor markets thus operate as complex adaptive systems in which aggregate outcomes emerge from decentralized interactions among heterogeneous participants. The present study accordingly conceptualizes ride-hailing participation as a networked adaptive process driven jointly by utility evaluation, threshold-based decision-making, and social learning.

3.2 Utility–Threshold Decision Mechanism

Rather than assuming utility maximization, this study argues that participation decisions are governed by a utility-threshold mechanism: drivers evaluate their current situation, form expectations about future opportunities, and compare the resulting utility against a minimum acceptable standard. We define the perceived utility of driver i at time t as

$$L_i(t) = R_i(t) - C_i(t) + B_i(t) + \lambda E_i(t),$$

where $R_i(t)$ denotes labor income, $C_i(t)$ participation costs, $B_i(t)$ platform incentives or subsidies, and $E_i(t)$ the driver's expectation of future market opportunities; λ measures the weight assigned to future expectations. Unlike conventional models focused on realized income, this formulation recognizes that participation is shaped by both current outcomes and anticipated returns. Labor income depends on market demand and competition among active drivers, while participation costs encompass direct labor inputs and indirect costs such as fatigue. Competition may extend working hours yet produce diminishing returns when supply exceeds demand.

Consistent with bounded rationality and satisficing behavior, drivers evaluate outcomes against a minimum acceptable standard rather than an optimum. We therefore introduce an individual participation threshold $\tau_i(t)$—the minimum utility required for continued engagement—capturing heterogeneous constraints including income requirements, opportunity costs, and risk tolerance. Participation decisions emerge formally as

$$S_i(t+1) = \begin{cases} 1, & U_i(t) \geq \tau_i(t), \\ 0, & U_i(t) < \tau_i(t). \end{cases}$$

When utility exceeds the threshold, the driver remains active; otherwise, the driver exits or reduces activity. The threshold thus functions as a decision boundary, and its dynamic comparison with utility generates feedback: market changes affect income and expectations, which update perceived utility, which triggers behavioral adjustments that alter competition intensity and feed back into future evaluations.

3.3 Network Learning and Behavioral Diffusion

Participation in platform labor markets is rarely an isolated process. Drivers are embedded in social networks through which they exchange information, compare outcomes, and learn from one another, making participation decisions dependent not only on individual utility but also on social interactions within local networks.

Social comparison theory suggests that individuals evaluate performance by comparing themselves with relevant others—a process especially important under uncertainty where objective standards are unavailable. Platform labor markets exhibit precisely these conditions: drivers frequently lack information about demand, algorithmic allocation, and future earnings, and thus rely on peers' observed experiences. Beyond information provision, social comparison generates perceptions of relative advantage and disadvantage. According to relative deprivation theory, dissatisfaction arises from unfavorable comparisons with reference groups rather than from low absolute outcomes. We define the relative deprivation of driver i as

$$RD_i(t) = \max\{0, U_i(t) - U_j(t)\},$$

where

$$\bar{U}_i(t) = \frac{1}{|N_i|} \sum_{j \in N_i} \bar{U}_j(t)$$

denotes the average utility within the driver's local neighborhood N_i. Relative deprivation thus emerges only when a driver's utility falls below the local reference level; the larger the gap, the stronger the perceived competitive pressure.

When drivers perceive competitive disadvantage, they learn from more successful peers by adopting participation patterns associated with superior outcomes—including longer hours, higher labor intensity, or delayed exit. To capture this,

we employ the Fermi updating rule: driver i adopts the participation pattern of neighbor j with probability

$$P_{i\to j} = \frac{1}{1+e^{-k(U_j-U_i)}}$$

where k denotes social learning intensity. When k is low, imitation is largely random; as k increases, drivers become more sensitive to performance differences and more willing to adopt successful patterns, diffusing competitive behaviors through the network via repeated learning.

Because drivers rarely replicate peers' behavior exactly, behavioral adjustment following successful imitation is governed by a Deffuant-style convergence mechanism:

$$a_i(t+1) = a_i(t) + \mu\left[a_j(t) - a_i(t)\right]$$

where μ denotes the behavioral convergence parameter. When $\mu \approx 0$,adjustments are minor; larger μ drives stronger behavioral alignment across the network. Accordingly, k governs the diffusion of competitive behaviors (imitation likelihood), while μ governs their synchronization (adjustment magnitude), together providing the micro-foundation for the emergence of collective involution.

3.4 Collective Involution: Definition and Formation

Ride-hailing drivers are among the most competitive groups in the platform economy. Facing declining earnings and growing uncertainty, drivers often extend working hours, reduce rest time, or remain active despite deteriorating conditions—strategies that frequently fail to generate sustained advantages when adopted collectively, producing what is described as labor involution. Across sociological and economic discussions, the concept uniformly emphasizes increasing inputs without commensurate improvements in outcomes: effort intensifies under competitive pressure while gains remain limited, reflecting a growing mismatch between effort and reward.

Building on Section 3.3, we conceptualize involution as a collective consequence of social comparison, relative deprivation, and network learning. Let $a_i(t)$ denote driver i's participation pattern. Through Fermi learning, driver i may adjust toward more successful neighbor j, changing participation intensity

$$\delta a_i(t) = a_i(t) - a_i(t-1),$$

and realized income

$$\delta R_i(t) = R_i(t) - R_i(t-1).$$

When only a small number of drivers intensify participation, temporary advantages may arise; but as similar patterns diffuse through the network, aggregate supply expands and competition intensifies, so drivers continuously increase labor input without obtaining proportional improvements—the central logic of involution.

We define *collective involution* as a state in which participation patterns become increasingly synchronized through social learning while the effectiveness of additional labor effort progressively declines. To operationalize this, we first define a network synchronization term:

$$S = \frac{1}{|E|} \sum_{(i,j)\in E} A_{ij}\sigma(\delta a_i \delta a_j),$$

where A_{ij} denotes the adjacency relationship between i and j, and σ denotes a bounded transformation function. Higher values of S indicate stronger behavioral alignment and wider spread of competitive strategies. Since synchronization alone does not imply involution if intensified participation still yields proportional returns, we also define the inefficient escalation term:

$$I = \frac{1}{N} \sum_{i=1}^{N} \sigma\left(\frac{\delta a_i}{\delta R_i} \cdot RD_i \cdot \delta a_i\right),$$

which is larger when drivers intensify participation under competitive pressure while obtaining only limited income improvement. The Collective Involution Indicator (CII) is then defined as

$$CH = S + I,$$

where ω controls the relative weight of both components (equal weights in the baseline). Higher CII values indicate that drivers are becoming behaviorally aligned while engaging in increasingly inefficient forms of competitive labor participation.

To assess aggregate labor efficiency, we introduce the **Marginal Return to Labor (MR)**:

$$MR = \frac{\delta R}{\delta H}$$

where $\delta H(t)$ represents the change in aggregate labor input. Declining MR signals that additional effort yields progressively smaller economic returns. Together, CII and MR capture the two defining dimensions of collective involution: behavioral synchronization through social learning, and declining effectiveness of intensified labor effort.

3.5 Computational Implementation

We implement the proposed framework as an agent-based model (ABM) representing the ride-hailing market as a decentralized system of heterogeneous drivers repeatedly interacting with market conditions and neighboring peers, through which macro-level patterns emerge from micro-level behavioral adaptations. Each driver is an autonomous agent with dynamic state variables:

$$A_i(t) = \{U_i(t), \tau_i(t), a_i(t), S_i(t)\},$$

where $U_i(t)$ denotes perceived utility, $\tau_i(t)$ the participation threshold, $a_i(t)$ the participation pattern (incorporating labor input, working intensity, and market persistence), and $S_i(t)$ market activity status. Agents are embedded in a social network $G = (V, E)$, where nodes represent drivers and edges carry information, observations, and behavioral influence; drivers observe and compare outcomes only within their local neighborhood, consistent with bounded rationality.

At each simulation step, active drivers receive earnings from demand–supply interaction, evaluate utility via the threshold mechanism (Section 3.2), and determine continued participation. Agents then calculate relative deprivation against neighborhood averages and probabilistically adopt more successful peers' participation patterns through Fermi learning (Section 3.3), allowing competitive behaviors to diffuse across the network. The simulation follows a sequential updating process as shown in Figure 1..

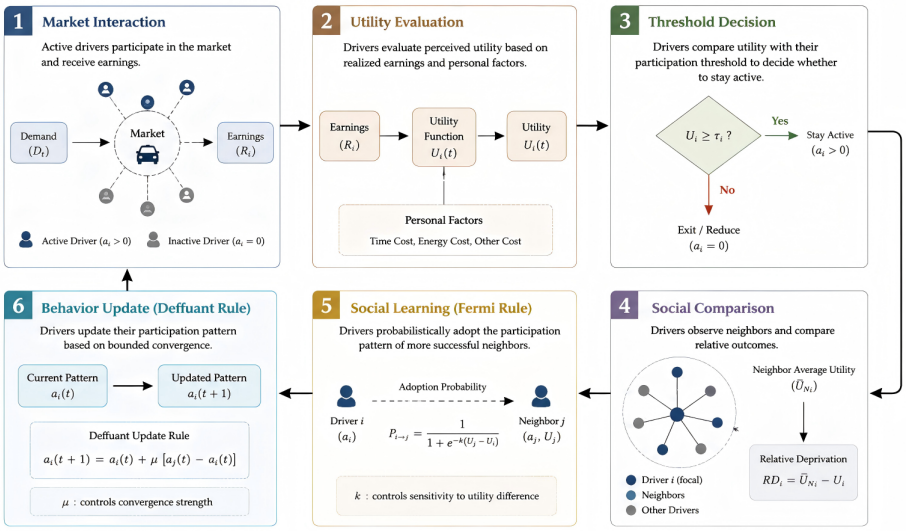

Fig. 1: The computational process of the utility-threshold social learning model for ride-hailing drivers

Repeated iterations generate the co-evolution of individual behavior and market conditions; though each driver adapts locally, collective consequences may differ substantially from individual intentions, enabling the model to capture involution as a system-level phenomenon. We track three output categories: the **Collective Involution Indicator (CII)**, which captures the diffusion and synchronization of imitation-driven participation patterns; the **Marginal Return to Labor (MR)**, which reflects the effectiveness of additional labor input; and

the number of active drivers, characterizing changes in market participation over time.

4 Experiments and Results

4.1 Experimental Configuration

Employing the agent-based framework of Section 3, the simulated ride-hailing market comprises heterogeneous driver agents in a small-world social network; at each period, drivers receive orders, earn income, compare outcomes with neighboring peers, and adjust participation intensity through utility-threshold evaluation and social learning, with individual adaptations aggregating into system-level labor market dynamics through repeated interaction.

The baseline simulation runs 1,000 drivers for 1,000 time steps under a fixed-demand environment, with labor supply evolving endogenously through drivers' behavioral decisions; orders are allocated by effective labor capacity and realized earnings determined by stochastic order prices after platform commission deductions—a setting that captures the structural characteristics of platform labor markets, where workers compete for limited demand under conditions of informational uncertainty and social comparison.

Table 4.1 summarizes the baseline parameter settings. Unless otherwise specified, these values are used throughout all experiments.

Table 1: Baseline Simulation Parameters

Parameter	**Description**	**Value**	**Parameter**	**Description**	**Value**
N	Number of drivers	1000	τ	Utility threshold	0.5
T	Simulation steps	1000	β	Imitation sensitivity	0.3
D	Daily market demand	15000	μ	Convergence parameter	0.5
ϕ	Platform commission rate	0.2	γ	Relative deprivation weight	0.5
f_0	Average Fare Pre-Order	20	λ	Future expectation weight	0.3

Five system-level indicators are tracked throughout the simulations: CII, MR,average labor intensity, average imitation probability, and relative deprivation,together capturing the behavioral, psychological, and economic dimensions of platform labor competition. The analysis proceeds in three parts: baseline evolutionary patterns and threshold effects; peer influence through variations in social learning parameters; and the roles of relative deprivation and future expectations.

4.2 Baseline Dynamics and Threshold Effects

To evaluate whether the proposed model can reproduce the core characteristics of collective involution in platform labor markets, we first examine the baseline

evolutionary dynamics under the parameter settings reported in Table 1. Figure 2 presents the baseline evolution of the Collective Involution Indicator (CII), Marginal Return to Labor (MR), and average labor intensity.

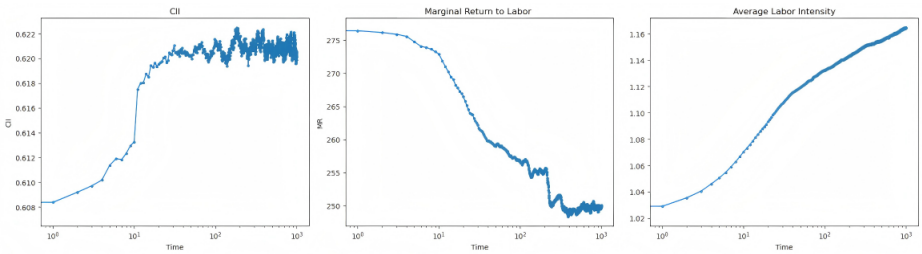

Fig. 2: Baseline Dynamics of Model

As shown in Figure 2, the CII increases rapidly during the early stage and subsequently stabilizes at a relatively high level, indicating the gradual formation of a persistent involutionary state. Meanwhile, the MR continuously declines, suggesting that increasing labor supply intensifies competition for a fixed pool of market demand and reduces the economic return of individual effort. Despite this decline, average labor intensity continues to rise throughout the simulation, implying that drivers respond to shrinking returns by supplying even more labor rather than withdrawing from the market. Together, these patterns capture the defining characteristics of collective involution and provide initial validation of the proposed model.

To further examine the role of utility threshold, we vary the mean value of the initial utility threshold distribution while keeping all other parameters unchanged. Figure 4.2 compares the long-run averages of CII, MR and labor intensity using the final 500 simulation steps.

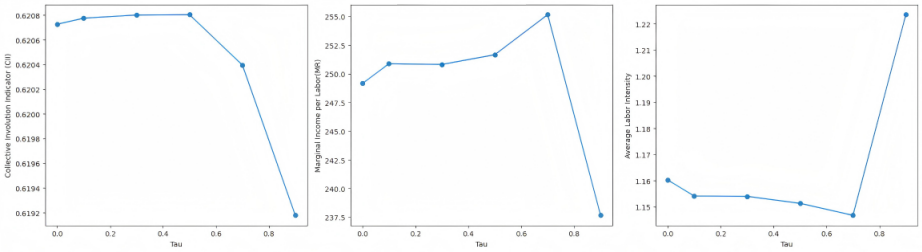

Fig. 3: Effects of Initial Utility Thresholds

As shown in Figure 3, increasing τ from 0.0 to 0.7 produces a gradual decline in CII accompanied by lower labor intensity and improved marginal returns, confirming that utility thresholds exert a systematic regulatory effect on system evolution. Higher thresholds weaken the tendency toward competitive escalation, reducing collective involution and improving labor efficiency.Notably, at $\tau = 0.9$ the system exhibits greater fluctuations—higher labor intensity but lower marginal returns—likely reflecting increased behavioral heterogeneity and

stochasticity when most drivers perceive their outcomes as satisfactory. Overall, utility thresholds serve as a key behavioral regulator linking individual aspirations to system-level outcomes, and higher thresholds generally mitigate involutionary dynamics.

4.3 Social Learning and Behavioral Convergence

Further, we examine the effects of two key behavioral parameters, the imitation sensitivity parameter (k) and the convergence parameter (μ), to investigate how peer-driven learning processes shape collective involution. The imitation sensitivity parameter governs the responsiveness of drivers to payoff differences when selecting peers to imitate, whereas the convergence parameter determines the extent to which drivers adjust their participation intensity following social interaction. By varying these parameters independently, we assess how social learning and behavioral convergence influence the emergence and evolution of collective involution.

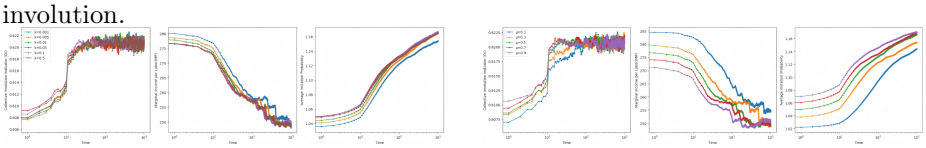

Fig. 4: Effects of Social Learning Parameters on Collective Involution Dynamics

As shown in Figure 4, both parameters influence collective dynamics, but theireffects differ substantially. Variations in k produce only modest changes in CII and MR—higher values slightly increase imitation probability, but evolutionary trajectories remain similar across settings, indicating that payoff-based imitation intensity alone has limited system-level impact. In contrast, μ generates more pronounced differences: higher values accelerate imitation probability growth, raise CII, and lower MR, indicating stronger collective competition and reduced labor efficiency. While k influences the likelihood of imitation, μ determines the magnitude of behavioral adjustment,conferring a substantially stronger impact on collective outcomes.

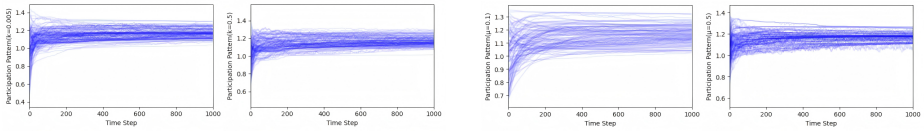

Fig. 5: Behavioral Convergence under Different Social Learning Parameters

Figure 5 further illustrates that, under different k values, drivers converge toward similar participation levels with a relatively stable behavioral distribution. Changes in μ, by contrast, substantially affect the speed and degree of convergence: higher values accelerate alignment and reduce dispersion,causing labor supply to expand more uniformly across the network and reinforcing competitive pressure. This convergence process provides a micro-level explanation for why increases in μ generate stronger involutionary dynamics and lower labor efficiency. Crucially, stronger peer influence does not arise from more frequent

imitation but from behavioral convergence: once participation patterns align, synchronized labor supply amplifies competition throughout the system.

4.4 Relative Deprivation and Future Expectations

While utility thresholds and peer influence explain the emergence of involution, they do not fully account for why drivers persist in intensifying participation under declining economic returns. We further examine two psychological mechanisms: relative deprivation (r), capturing dissatisfaction from unfavorable peer comparisons, and future expectation (λ), reflecting anticipated income improvements. Figure 6 reports their evolutionary effects on CII and MR.

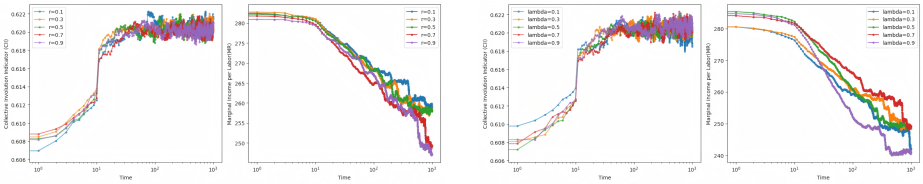

Fig. 6: Effects of Relative Deprivation and Future Expectation on Collective Outcomes

As shown in Figure 6, variations in both parameters produce only minor differences in CII evolution—the system converges to similar levels of collective involution across settings, suggesting that involution emergence is robust to changes in individual psychological perceptions. Both parameters exert a more noticeable influence on MR: higher relative deprivation and stronger future expectations are associated with faster declines in labor returns and lower long-run labor efficiency, indicating that psychological factors play a secondary role in determining involution intensity but substantially affect the economic consequences experienced by workers.

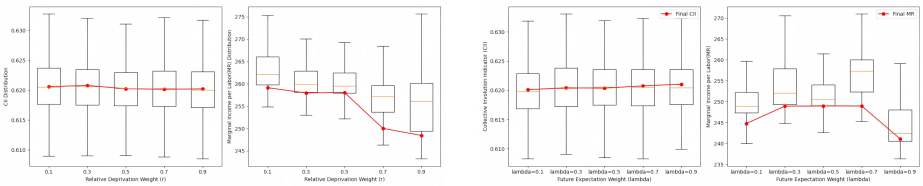

Fig. 7: Long-run Distributions and Tail Averages under Different Psychological Parameters

Figure 7 confirms this pattern from a long-run perspective. CII remains remarkably stable across different psychological parameter settings, while marginal returns exhibit considerably greater sensitivity. Higher relative deprivation is associated with steadily declining labor efficiency, while excessively strong future expectations ($\lambda = 0.9$) produce a pronounced reduction in marginal returns, suggesting that overly optimistic anticipation encourages sustained labor expansion despite diminishing economic rewards. Psychological factors thus primarily shape the economic costs of involution rather than its emergence: while social

learning and behavioral convergence drive the formation of collective involution, relative deprivation and future expectations determine how costly such competition becomes for individual workers.

4.5 Discussion

The results reveal three principal findings. First, utility thresholds function as a behavioral filtering mechanism, reducing drivers' willingness to intensify participation under unfavorable conditions and thereby limiting excessive labor escalation. Second, and most importantly, behavioral convergence exerts the strongest influence on collective involution: while imitation sensitivity (k) affects learning probability, convergence (μ) synchronizes participation patterns across the network, producing more homogeneous labor supply and intensified market competition—indicating that involution emerges primarily through behavioral alignment rather than imitation frequency. Third, peer influence operates through social interaction rather than psychological motivation: once social learning begins to synchronize participation behaviors, collective competition becomes largely self-reinforcing, highlighting the primacy of network-based mechanisms over individual psychological factors.

From a practical perspective, excessive labor competition cannot be alleviated solely through income incentives or individual-level interventions. Because involution is driven by collective behavioral convergence, platform governance should direct greater attention to information diffusion, social learning environments, and the mechanisms through which workers form participation expectations; managing competitive synchronization may be as important as improving individual earnings conditions.

5 Conclusion

This study develops a utility-threshold agent-based model to examine how peer influence shapes ride-hailing drivers' market participation and contributes to collective involution. Simulation results demonstrate that involution can emerge endogenously through decentralized behavioral adaptation: as drivers continuously adjust participation intensity under social comparison and learning, labor supply expands while marginal returns decline, and higher utility thresholds generally reduce excessive escalation and improve labor efficiency.

The study contributes to the literature in three ways. First, it extends platform labor research by introducing a utility-threshold mechanism linking aspiration-based evaluation to participation decisions. Second, it demonstrates peer influence as a central driver of involutionary competition; crucially, the results reveal that behavioral convergence is substantially more influential than imitation sensitivity, suggesting that synchronized adaptation rather than imitation frequency constitutes the key mechanism underlying collective involution. Third, it provides a computational framework connecting individual behavioral adaptation with emergent labor-market dynamics.

Future research may incorporate more complex network structures, heterogeneous platform governance mechanisms, and dynamic demand environments to better capture the diversity of real-world platform ecosystems. Extending the framework to other forms of digital labor may further improve understanding of how social learning and adaptive behavior shape collective outcomes in platform-mediated labor markets.

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