Role polarization and its effects in the spatial ultimatum game

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Human society is believed to be becoming increasingly polarized, yet it remains unclear how role polarization influences the evolution of fairness. In addition, little is known about role adaptation, despite the fact that altering the roles of players can often change the outcome of the ultimatum game. Unlike earlier static, random, symmetric role assignment, here I suggest a succeed-reinforce–fail-slacken role adaptation rule that encourages successful proposers in the present round to propose again in the next round and vice versa. The results demonstrate that this simple rule can tip the scales in favor of fair strategies when it comes to the proposer advantage, and therein lies the key to promoting fairness. Depending on its pace, notably, role adaptation can direct the system to equilibrium states that bear variable degrees of role polarization, with two consequences incidentally. Not only does it favor fairness, it also fosters empathy. Noise associated with role adaptation often reduces role polarization and thus has a negative impact on fairness and empathy. The comparison of experiments with various networks validates the substantial resilience of role polarization to structural changes. These findings add to the evidence for role polarization and highlight the centrality of role adaptation in the evolution of fairness.

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I. INTRODUCTION

Human civilization is a long process of development advancing towards fairness. In our ancestral past, fairness preference was found in collective hunting [1] and food sharing [2]. In contemporary life, it is more needed than ever to address climate change [3] and maintain the international trade order [4]. Determining why social animals display fairness to others, especially to unrelated strangers, is a daunting challenge that spans several academic areas [5]. An economic game experiment called the ultimatum game has been used repeatedly to address this issue ever since Güth *et al.* published their experimental results [6]. The game puts forward a task in which two players allocate a free resource; therein lies a role constraint that one acts as the proposer and the other as the responder. The proposer first initiates a proposal on how to divide the money, while the responder must respond to it. Depending on the responder's response, there are two possible outcomes: Either the responder acknowledges the proposal and they share the money as agreed or the responder rejects the proposal and they end up with nothing [7].

For the one-shot ultimatum game, the game-theoretic solution is twofold, due to the role imbalance between the two players involved in this game. The best choice is for the proposer to make the minimum possible proposal while the responder accepts any nonzero proposal. Despite the soundness of the solution, it is far from satisfactory from a fairness perspective [8]. Not only that, it also fails to align with empathy, the ability to put oneself in another's place [9–11]. Conversely, recent years have witnessed a shift in the equilibrium towards an ideal split, as evidenced by data from both the field and the laboratory [12]. This mismatch thus raises questions as to what drives proposers to offer much more than previously predicted and why vetoing unfair proposals can nevertheless be solidly endorsed even if there is no clue that doing so would confer immediate benefits on the player.

Prior work has made great progress in mitigating this mismatch. Research showed that the fate of fair strategies in latticed games is usually better than that in nonspatial games [13]. Likewise, the status of network metrics, such as the clustering coefficient, disorder, degree distribution, and the like, as determinants of fairness was underlined [14]. Rather than static structure, the coevolutionary ultimatum games on mini dynamic networks demonstrated that fairness can prevail as long as partner optimization occurs frequently enough, either for profit maximization [15] or due to the failure of resource sharing [16]. Beyond networks, insights may have been gained from the way natural selection operates on the strategy [17]. In this instance, high rejection willingness was still observed under individual selection, despite the absence of group selection and cultural selection. Additionally, the study of assortment patterns contended that positive assortment has limited effect on fairness, whereas negative assortment might reinforce fairness in a way that allows spite to evolve [18].

The answer to the fairness dilemma also touched on how fairness is entangled with other norms. One such norm is empathy, and the belief that empathetic people may be less unfair is a central hypothesis of this stream of research. Rethinking the game in a perspective-taking fashion, the prior work defined a class of empathetic strategies [19]. Its findings reflected a dramatic enhancement to a fair split even if a tiny percentage of players stick to such strategies. Latter, a similar goal was achieved in the grouped population [20]. In

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particular, it was elucidated that the use of a strategy space with discretization and empathy can instantiate a kind of defense effect in favor of fairness [21].

Nonetheless, it remains interesting to see how roles and strategies coevolve and to what extent this coevolution reshapes fairness, especially in light of the fact that a successful split in this game depends not only on the strategies of the two players involved, but also on which of them assumes the position of proposer [9,10,22–24]. In earlier ultimatum games and dictator games, however, attention was concentrated predominantly on static, random, and symmetric role assignments. This focus may lead to a neglect of asymmetry and an underestimation of the adaptive nature of living things. Further, there is substantial evidence to support this assertion in real life, such as the inherent ability of cells to adapt morphologically and functionally to their ever-changing surroundings in order for proper development and function of central nervous systems [25]. In this sense, these approaches sometimes fail to provide a realistic perspective. It is thus urgent to clarify how a player's role evolves in this game and to what extent role evolution affects fairness. In this article, I frame my investigation by raising two primary hypotheses. First, I hypothesize that each player has an independent aspiration as to whether or not to act as a proposer, reflecting social diversity. Second, I hypothesize that players are free to fine-tune their aspirations according to the outcome of the game, like biological adaptation. In doing so, I suggest a feedback-based rule to improve the role assignment of ultimatum games. The results show that role adaptation can lead to role polarization in favor of fairness and empathy. Frequently, the faster the role adaptation, the higher the role polarization and the fairer the split. It is worth emphasizing that the generation of role polarization as well as its impact is not influenced by network structure.

II. MODEL

The population structure is characterized by Barabási-Albert scale-free networks [26], $L \times L$ lattices with von Neumann neighborhood and periodic boundary conditions [27], and Erdős-Rényi random graphs [28], respectively. Let me briefly describe how to create a Barabási-Albert scale-free network. I first establish a fully connected graph of m_0 nodes. Second, a preferential attachment growth method is used to link a new node to m ($m \leqslant m_0$) existing nodes. So the total number of edges M and the total number of nodes N meet $M = (N - m_0)m + \frac{m_0(m_0-1)}{2}$. Specifically, the probability that a newly added node would choose an existing node x as its neighbor is given by the formula $k_x / \sum_{y\in\Omega} k_y$, where k_x is the degree of node x and Ω is the set of all existing nodes. As for constructing a random graph, I directly use M links to pair N nodes at random.

Each player occupies a node and is assigned two initial parameters p_i and q_i, uniformly and randomly extracted from the range of $[0, 0.5]$ like in Refs. [7,16,23]. The subscript represents the ith player. Here p_i is the portion that i supplies to their opponent when in the role of proposer and q_i is i's acceptance threshold when in the role of responder. The pair (p_i, q_i) represents i's strategy in the ultimatum game. The sum divided in each game is specified to be 1. As for role allocation, a parameter Λ_i is added to represent i's aspiration for being a proposer. This value is randomly chosen from the unit interval. Here $\Lambda_i \to 1$ (0) implies that i is becoming more (less) eager to assume the position of proposer. Importantly, players are free to modify their aspirations in accordance with the success or failure of resource allocation.

Three essential components make up a typical Monte Carlo simulation: playing the game, adjusting aspirations, and updating strategies. An agent i is first chosen at random from the population and initiates a resource allocation. If i has no neighbors, another agent is chosen again. Otherwise, i picks out one of their neighbors at random, j, and they engage in an ultimatum game. In this game, i is assumed to take the role of proposer with a probability given by Λ_i. Specifically, a real number is drawn at random from the unit interval. If it is less than Λ_i, i (j) is designated as the proposer (responder). If not, the roles are assigned in the opposite way. It is easy to see that even without role adaptation, this role assignment is different from the previous symmetric method. The payoffs ψ_i that i harvests in an ultimatum game can be calculated by either

$$\psi_i = \begin{cases} 1 - p_i, & p_i \geqslant q_j \\ 0, & p_i < q_j \end{cases} \tag{1}$$

when in the role of proposer or

$$\psi_i = \begin{cases} p_j, & p_j \geqslant q_i \\ 0, & p_j < q_i \end{cases} \tag{2}$$

when in the role of responder

The iteration moves to the following step after the game and fitness calculation, where the actual proposer of i and j is allowed to revise their aspiration as follows:

$$\Lambda_x = \begin{cases} \Lambda_x + \lambda, & p_x \geqslant q_y \\ \Lambda_x - \lambda, & p_x < q_y. \end{cases} \tag{3}$$

Here $x, y \in \{i, j\}$. The parameter λ measures the sensitivity of adaptation. The larger the value of λ, the faster the adaptation of aspiration. This formula tells a straightforward logic, which says if a player succeeds (fails) in proposing, it will raise (lower) their morale for subsequent proposals. In this way, an in-game feedback is established between role allocation and resource allocation, as in Ref. [29]. Hereafter, it is referred to as the succeed-reinforce–fail-slacken (SRFS) rule. Note that $\Lambda_i \in [0, 1]$, so whenever Λ_i hits the extreme value 0 or 1, it can only change in the other direction.

When it comes to the strategy update section, player i renews their strategy by learning a randomly chosen neighbor j with the probability specified by the Fermi function [30,31]

$$T(s_j \to s_i) = \frac{1}{1 + \exp[-(\Pi_j - \Pi_i)/K]}, \tag{4}$$

where Π_i (Π_j) is the total payoff of i (j) and K is the selection intensity; $K \to \infty$ means random drift, whereas $K \to 0$ indicates that high-yielding strategies are more likely to prevail. The learning error enters the strategy update to mimic a trembling hand effect [7,13,14] as follows:

$$\begin{aligned} p_i &= p_j + \xi_p, \\ q_i &= q_j + \xi_q. \end{aligned} \tag{5}$$

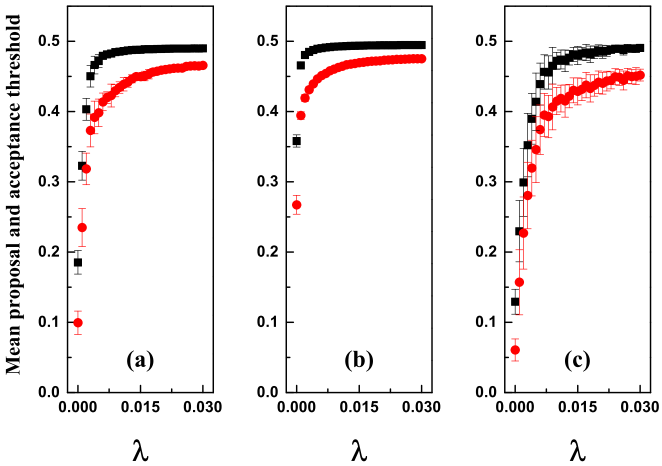

FIG. 1. Average proposal level $\bar{p}$ (black squares) and average acceptance threshold $\bar{q}$ (red circles) by the pace of role adaptation λ with regard to (a) the Erdős-Rényi random graph, (b) the square lattice, and (c) the scale-free network. The other parameters are $N = 1000$, $M = 2000$, $L = 40$, $K = 0.1$, and $\mu = 0.01$.

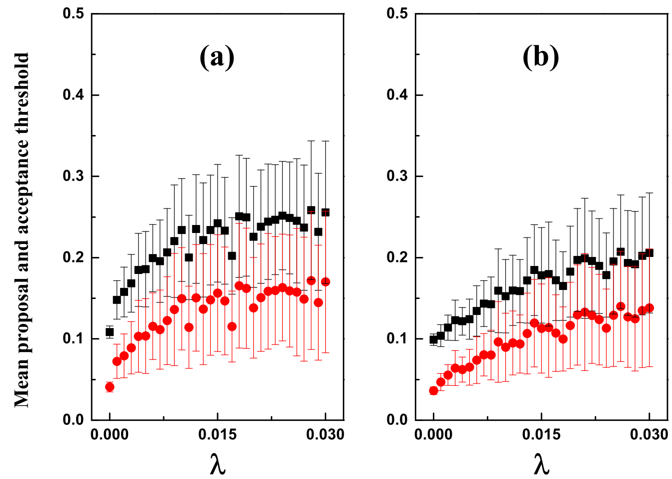

FIG. 2. Average proposal level $\bar{p}$ (black squares) and average acceptance threshold $\bar{q}$ (red circles) by the pace of role adaptation λ under the mean-field-like interaction. In each time step, everyone plays against four other randomly selected players and updates the strategy by learning the strategy of another randomly selected player. The results are by the (a) average and (b) additive payoff. The other parameters are $N = 1000$, $K = 0.1$, and $\mu = 0.01$.

Without losing generality, the values of ξ_p and ξ_q are drawn uniformly and independently from the interval $[-0.005, 0.005]$ in this investigation. In addition, with probability μ independently in each time step, Λ_i is reset to a value uniformly and randomly drawn from the interval [0, 1] to simulate a noise in adaptation, when player i updates their strategy.

Each player is chosen on average once each full iteration to set up a game, update aspiration, and update strategy. After a sufficient transition time (typically 10 000 full time steps), the average proposal level $\bar{p}$ and the average acceptance threshold $\bar{q}$ are determined by averaging an additional 10 000 iterations for 50 independent runs.

III. RESULTS AND DISCUSSION

A. Coevolution of fairness and empathy

I first review the relationship between strategy evolution and role evolution with regard to three different kinds of networks. Figure 1 demonstrates how the average proposal level $\bar{p}$ and the average acceptance threshold $\bar{q}$ relate to the pace of role adaptation. Note first that when role adaptation accelerates, players tend to share more resources in the role of proposer and simultaneously they grow less tolerant of unfair offers as well in the role of responder. Here a fair split like half-to-half can never come true unless players adapt their roles with a relatively fast SRFS adaptation. For lattices, Erdős-Rényi graphs, and scale-free networks, the value of $\bar{p}$ can be increased by 38.15%, 164.31%, and 279.49%, respectively, when λ grows from 0 to 0.03. The same pull-up effect also applies to the value of $\bar{q}$, with the ratios of improvement for the above three networks being 77.81%, 368.50%, and 645.15% respectively. The SRFS rule thus provides an alternative approach to achieve a fair split in the ultimatum game from the perspective of role evolution. In addition, the upward trend of λ most of the time results in a narrowing gap between the $\bar{p}$ curve and the $\bar{q}$ curve in this plot. This means that, aside from promoting fairness, the SRFS rule instantiates an enhancement to empathy too. It is worth noting that this is not trivial, although there is already some evidence for the coevolution of fairness and empathy, because most likely it points to a new symbiosis of fairness and empathy, in the sense that the two norms have successfully coevolved under the premise that they had no prior connection as opposed to the previous hypothesis that one was pre-positioned to have a specific effect on the other in advance [19–21].

The topology of the interactions plays a crucial role in how cooperation and fairness evolve [32,33]. Note that the game dynamics in Fig. 1 may have been disentangled from the topology of the interactions because of the current payoff calculation method. So it remains necessary to see how the game dynamics shifts when considering the mean-field-like interaction (see Fig. 2) and other types of payoff such as the average payoff [34] [see Figs. 2(a) and 3(a)–3(c)] and the additive payoff [33] [see Figs. 2(b) and 3(d)–3(f)]. Although role adaptation still enhances fairness in Fig. 2, the values of $\bar{p}$ and $\bar{q}$ are lower than those in networked games, highlighting the role of the topology of the interactions in facilitating fairness in this context. Under the average payoff, moreover, the game dynamics readily shares great similarity across different networks. Under the additive payoff, however, the game dynamics of the scale-free network shows a remarkable discrepancy from that under the average payoff. This means that the scale-free network has a greater impact on the way fairness emerges than other networks in this study due to its significant degree of heterogeneity. Unless otherwise stated, subsequent analyses are based on Erdős-Rényi random graphs.

B. Role polarization

To shed light on how the SRFS rule affects players' aspirations to assume the proposer role, Fig. 4 depicts how the average aspiration of the population changes with the pace

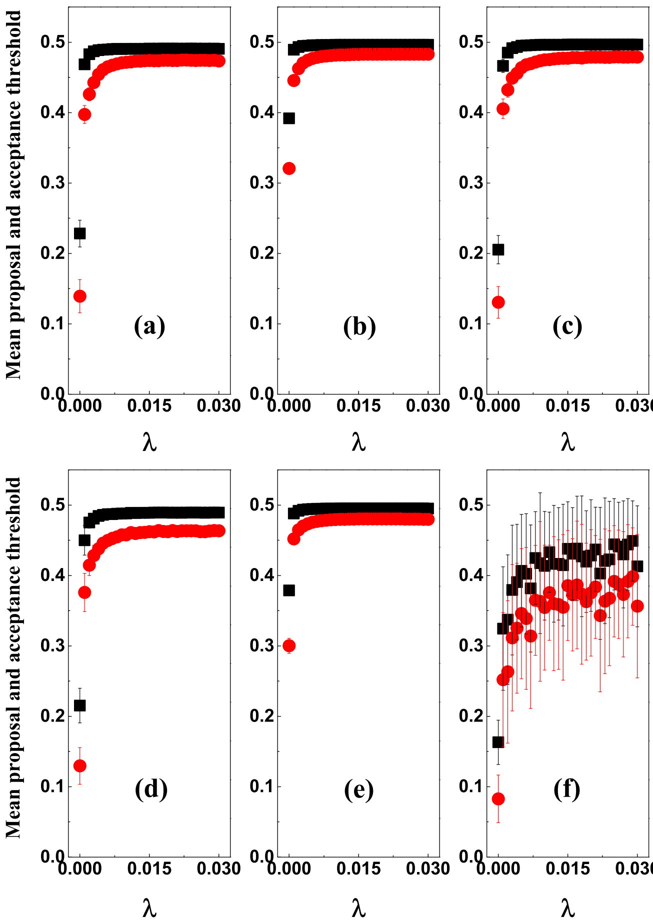

FIG. 3. Average proposal level $\bar{p}$ (black squares) and average acceptance threshold $\bar{q}$ (red circles) by the pace of role adaptation λ with regard to (a) and (d) the Erdős-Rényi random graph, (b) and (e) the square lattice, and (c) and (f) the scale-free network. The results are by the (a)–(c) average and (d)–(f) additive payoff. The other parameters are $N = 1000$, $M = 2000$, $L = 40$, $K = 0.1$, and $\mu = 0.01$.

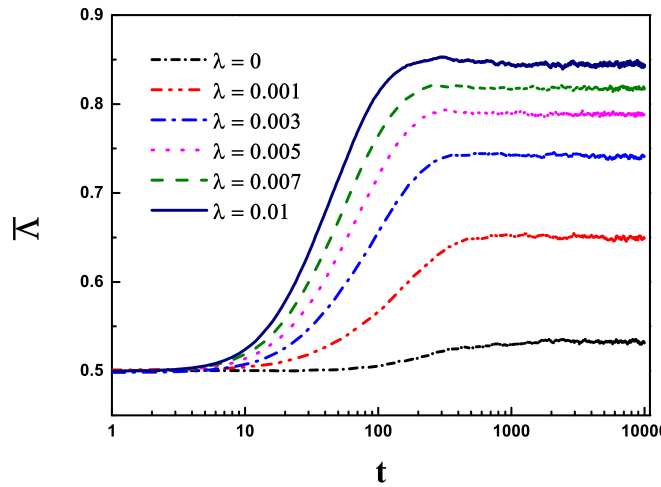

FIG. 4. Representative role polarization induced by role adaptation at various speeds. The other parameters are $N = 1000$, $M = 2000$, $K = 0.1$, and $\mu = 0.01$.

at which players adapt their roles. I observe an intriguing and infrequently occurring role polarization. I attribute this phenomenon to the long-standing intertwining between role evolution and strategy evolution. Under the guidance of the present method, evolutionary dynamics often drives players to take on more proposer roles in their games. Further, it is interesting to see that this trend is linked to how fast players adjust their roles. Generally, $\bar{\Lambda}$ converges to a different level provided λ takes distinct values. The initial baseline $\bar{\Lambda} = 0.5$ means that the population is neutral about whether to act as a proposer in the game, like the random rule [9,10] or in Ref. [21] where each player acts once as a proposer and once as a responder. In contrast to the absence of SRFS adaptation and slow SRFS adaptation, rapid SRFS adaptation usually results in a unanimous desire for the position of the proposer that is making players' roles more divided. Especially when λ is remarkably larger than 0, $\bar{\Lambda}$ can reside at a point strikingly above the baseline. In this sense, the spontaneous consensus of the players' willingness to propose can be interpreted as a manifestation of role polarization, precisely, a kind of role unipolarization. It always arises when a larger λ value is considered, independent of the network. Hence, the SRFS adaptation in this study instantiates a solid pathway to role polarization for the ultimatum game, hidden behind the coevolution of roles and strategies of this game.

Next I examine how the SRFS rule influences players' proposing behavior. For the sake of analysis, I divide the strategy space into five different intervals and use s_1, s_2, s_3, s_4, and s_5 to denote the strategies whose offers fall in (0, 0.1), (0.1, 0.2), (0.2, 0.3), (0.3, 0.4), and (0.4, 0.5), respectively. Figure 5 shows how the average fraction of strategies, the average aspiration of the population, the average fraction of successful proposals from different strategies, the average offer, and the average acceptance threshold in each time step vary with the pace of role adaptation. Note first that there are two different kinds of equilibrium states. One is the coexisting state where two or more types of strategies coevolve and the other is the absorbing state where only one type of strategy predominates. Which state the system will eventually stabilize in depends precisely on the pace of role adaptation. When role adaptation speeds up, there exists a transition of the equilibrium state from the coexisting state to the absorbing state. In fact, being appointed as a proposer may sometimes be a good sign in a one-shot ultimatum game. If a proposer fails to satisfy a responder, neither player loses more than the other because they both get nothing in this case. If not, the proposer may build a fitness advantage by keeping more of the money for themself. Nevertheless, this role-related advantage does not favor one strategy over another under the symmetric and random role assignment settings because of near-equal proposal probabilities among players at this point.

In the backdrop of role adaptation, the situation is speculated to change. The information provided by Fig. 5 lends credence to this speculation. Recall that fair players are always willing to transfer more shares to their opponents, so they are statistically more likely to succeed than unfair ones when making proposals. As a result, under the direction of the SRFS rule, the aspirations of high-proposal strategies tend to increase, while those of low-proposal strategies tend to decrease. This difference will cause an imbalance between

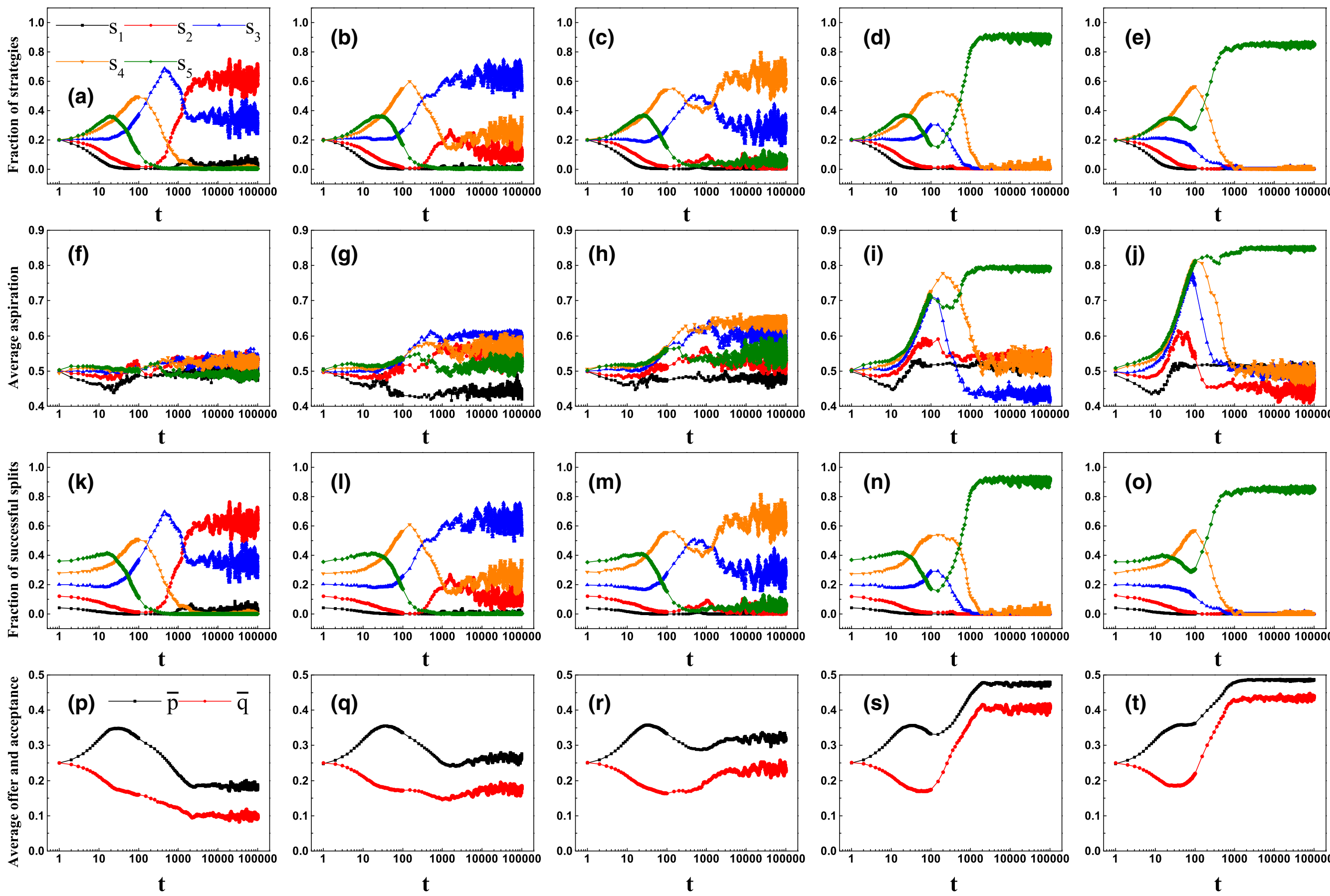

FIG. 5. Time series of (a)–(e) the average fraction of strategies, (f)–(j) the average aspiration of players with different strategies, (k)–(o) the average fraction of successful proposals from different strategies, and (p)–(t) the average offer and the average acceptance threshold, with regard to different values of λ. In columns from left to right the values of λ are 0, 0.0005, 0.001, 0.005, and 0.01, respectively. The s_1, s_2, s_3, s_4, and s_5 label the strategies whose proposals fall in (0, 0.1), (0.1, 0.2), (0.2, 0.3), (0.3, 0.4), and (0.4, 0.5), respectively, regardless of the values of q and Λ. The other parameters are $N = 1000$, $M = 2000$, $K = 0.1$, and $\mu = 0.01$.

fair and unfair strategies at the level of grasping the proposer edge. Not only that, as role evolution and strategy evolution intertwine frequently with each other, such imbalance is prepared to persist and even be amplified. In addition, role reshuffling will not stop throughout this process unless role polarization emerges eventually. As shown in Figs. 5(f)–5(o), the more quickly the role evolves, the more lopsided the proposer's advantage grows. To summarize, role evolution in its suitable entanglements with strategy evolution can confer a compounding advantage akin to the Matthew effect [35] on fair strategies, thereby reversing the original competitive ordering of strategies in this game and leading resource sharing to a near-fair division.

C. Impact of noise associated with role adaptation

Real systems suffer from noise and interference from time to time. In view of this, a kind of noise is taken into account to simulate uncertainty in role adaptation as detailed in Sec. II. Next I focus on its influences. Owing to its potential negative impact, especially with respect to the precision and effectiveness of role adaptation, it may be a key element pertaining to the progression to role polarization. Regardless of network structure, as demonstrated by Fig. 6, the values of $\bar{p}$ and $\bar{q}$ generally drop monotonically with steep-descent slopes as this noise gradually grows stronger. Not only that, it inhibits

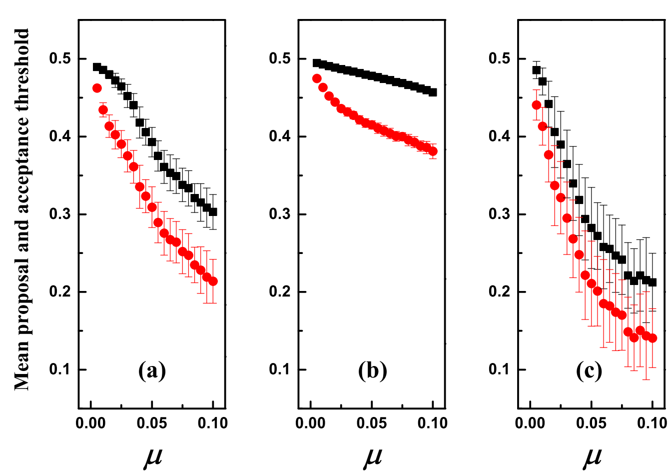

FIG. 6. Average proposal level $\bar{p}$ (black squares) and average acceptance threshold $\bar{q}$ (red circles) by noise μ with regard to (a) the Erdős-Rényi random graph, (b) the square lattice, and (c) the scale-free network. The other parameters are $N = 1000$, $M = 2000$, $L = 40$, $K = 0.1$, and $\lambda = 0.01$.

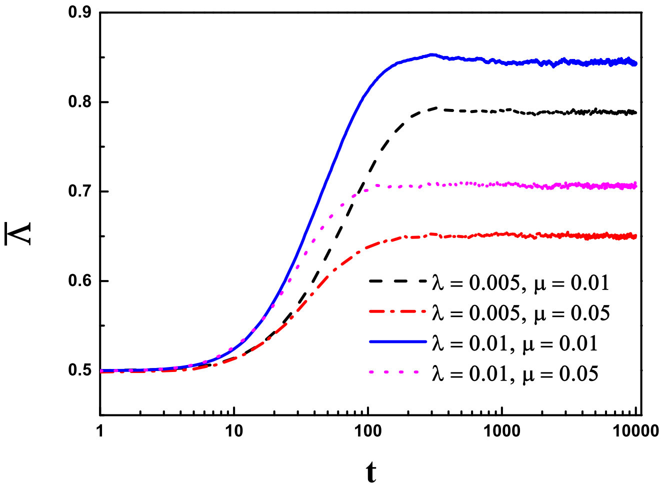

FIG. 7. Typical role polarization by noise μ. Note that slow role adaptation at low noise can outperform fast role adaptation at high noise in enhancing role polarization. The other parameters are $N = 1000$, $M = 2000$, and $K = 0.1$.

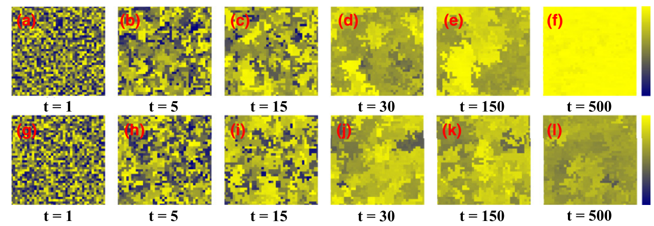

FIG. 8. Evolution of proposals when (a)–(f) $\lambda = 0.01$ and (g)–(l) $\lambda = 0$ in the square lattice. Prior to the onset of evolution, the proposal of each player is randomly drawn from the interval [0, 0.5], with their acceptance threshold being randomly chosen from the interval [0, 0.5]. The other parameters are $L = 40$, $K = 0.1$, and $\mu = 0.01$.

empathy too as revealed by the widening gap between the two curves, especially for the lattice structure. Meanwhile, the square lattice exhibits the least overall downregulation of $\bar{p}$ and $\bar{q}$ across the considered noise range among the three networks. Figure 7 explains why such noise impairs fairness and argues that it has to do with the noise-induced reduction in role polarization. In this regard, noise in role adaptation therefore goes against the observation obtained in Figs. 1 and 5 that the stronger the role polarization, the better the evolution of fairness and empathy.

D. Expansion of fair alliances

The cluster effect [36], a dynamical process associated with pattern formation [21], is one of the most important survival strategies for altruists. Next I further account for how role adaptation works from a micro perspective. Before looking into this issue, it is necessary to introduce the concept of near-fair players. They refer to those with relatively high offers and acceptance thresholds (for instance, greater than 0.4). The survival of such players prior to the population becoming significantly polarized will be illustrated to have a great deal to do with the equilibrium state's fairness level in this article. Figure 8 displays characteristic invasions in the square lattice with and without role adaptation. In either case, locally dominant players immediately engulf adjacent ones by disseminating their strategies to them at the onset of evolution, resulting in the emergence of numerous small strategy clusters. Inside these patches, players bear similar strategies and the proposal level exceeds the acceptance threshold, a basic feature of networked ultimatum games [13]. It is generally assumed that the analysis of the predations chain between these clusters can shed light on the resulting pattern formation as well as its function in evolution, thereby illuminating how the mechanism plays its role.

I start by going through what occurs when the players' roles become polarized. From this stage on, near-fair alliances start to expand quickly because they usually take the lead in competition against others if players' roles are frozen by the SRFS rule. This view is supported by two points. First, near-fair proposers on the cluster boundary are predicted to be successful proposers since their pretty high proposals can frequently meet the expectations of responders from another cluster. Given the iterative effect of evolution, they will benefit a great deal from this even though the edge in a single round may be marginal owing to their high proposals. Yet in a reversal of roles, second, near-fair players are prepared to reject their rivals in most cases, thus depriving the latter of the original proposer advantage. By this logic, under the SRFS hypothesis, it can be said that players on the frontiers of the aforementioned near-fair clusters are more evolutionarily viable than those from other clusters. Consequently, the main obstacle to fairness now becomes how to keep these near-fair strategies alive, before the population exhibits considerable role polarization. In addition, the results from earlier in this article show that the key to resolving this obstacle is directly linked to the pace at which players adapt their roles. As shown in Fig. 5, evolutionary dynamics usually renders these near-fair strategies unviable when role adaptation is absent or occurs at a sluggish pace. By comparing the results in Figs. 8(l) and 8(f), it is not difficult to find that the stationary level of fairness at this point is often lower than that of fast SRFS adaptation.

To better understand the story behind this mechanism, Fig. 9 illustrates a typical intrusion of a near-fair cluster into an unfair population. Figures 9(a)–9(h) describe how players' strategies evolve, while Figs. 9(i)–9(p) trace how players' roles adapt. Although a player can reap more payoff by behaving selfishly or unfairly in the early game, at the same time, the player is also faced with the risk of losing the opportunity to act as a proposer in the future game. Conversely, players with higher proposals will win more chances to be the proposer, just as players with a good reputation will win more chances to be the dictator [24]. The snapshots convey that under the guidance of the SRFS rule, fair players are becoming more aspirational, while unfair players are suffering a persistent aspiration slump. So it suggests a Matthew effect, where ambitious players, often fair, are prepared to propose more frequently and grow more ambitious. As discussed above, this pattern of mutual adaptation between roles and strategies turns out to be in great favor of the evolution of fairness and empathy in ultimatum games.

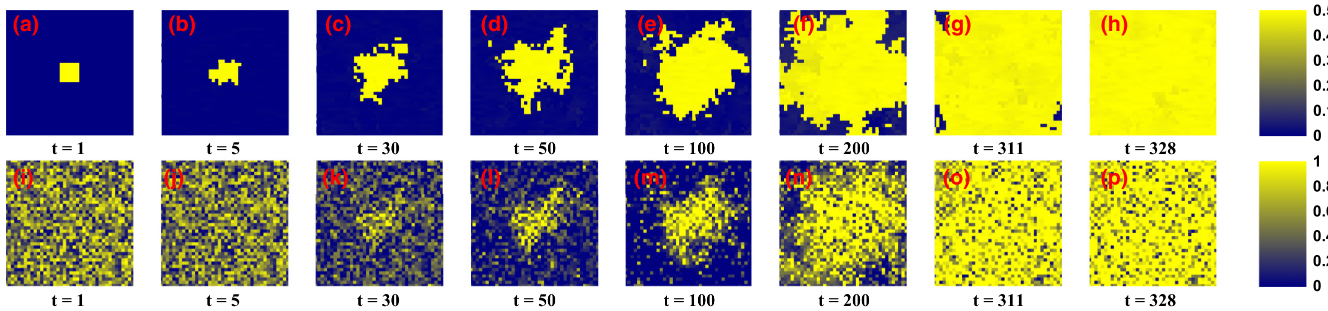

FIG. 9. Expansion of fair alliances through the coevolution of roles and strategies under the influence of the SRFS rule in the square lattice. The evolution of proposal is traced in (a)–(h), whereas the evolution of aspirations is captured in (i)–(p). Before the evolution starts, a 6×6 fair cluster is seeded in the lattice, with $p = q = 0.5$ within the cluster. The other parameters are $L = 40$, $K = 0.01$, $\lambda = 0.01$, and $\mu = 0.01$.

IV. SUMMARY

Role splitting plays an important part in shaping the evolution of fairness in the ultimatum game [9,10,22–24,37]. This article studied a spatial ultimatum game with role adaptation to understand how role polarization arises and how it influences the evolution of fairness. In order to bridge the gap between role splitting and resource sharing in this game, a SRFS role adaptation rule was recommended. The results showed that the coevolution of fairness and empathy can be dramatically enhanced if players follow this straightforward rule to adapt their roles in response to in-game feedback. Different from prior static, random, and reputation-based role assignment [9,10,23,24], role adaptation has been shown to be able to induce role polarization depending on its pace. Further, role polarization has been revealed to underpin fairness in a way that allows fair players to exploit more proposer advantage. Under the role adaptation hypothesis, the solution to this dilemma can be transformed into answering how to sustain near-fair strategies before the population grows highly polarized. This relies much on how quickly players adapt their roles in evolution. Finally, it indicates that the generation of role polarization and its effects are pretty robust to the population structure. These results create a strong connection between role evolution and strategy evolution of ultimatum games.

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