Cooperation dynamics in multi-issue repeated social dilemma games with correlated strategy

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In the real world, individuals are often involved in collaboration on multiple issues, and these issues may interact with each other. Given the complexity of the interaction, we establish a multi-issue repeated game model, in which individuals participate in multiple social dilemma games simultaneously and repeatedly, and strategies in different issue games are correlated and reactive. We explore the cooperation dynamics of strategies in the population from a multiobjective perspective, in which an individual's preference for each issue is described by a weight vector, and heterogeneous preferences of individuals in the population are also considered. Through simulations on two-issue games, we find that compared to the uncorrelated case, the correlated strategy can significantly promote cooperation in both games regardless of which issue players prefer. Under the condition of homogeneous preference, an increase in the payoff weight of a given issue decreases the level of cooperation in that issue, and the optimal condition to sustain cooperation to the maximum extent is when the payoff weights of all issues are equal. Moreover, under the condition of heterogeneous preference, there exists an optimal proportion of players with different preferences under which the cooperation rate can reach its highest level in the population. This work highlights individual trade-offs on different issues when engaging in multiple games simultaneously and further enriches the research of evolutionary games from a multiobjective and correlated strategy perspective.

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I. INTRODUCTION

Cooperation plays a very important role in microbial populations and human societies [1–3]. For example, bacteria can resist external invasions by cooperating [4], and the cooperation of humans can significantly improve the quality and efficiency of task completion [5]. However, according to classical Darwinian evolutionary theory, rational individuals are more inclined to maximize their benefits, leading to the breakdown of cooperation and tragedy of the commons [6]. This results in a social dilemma. A common theoretical framework for studying social dilemmas is evolutionary game theory, with a particular focus on the prisoner's dilemma game [7–13]. Understanding the emergence and sustainability of cooperation has therefore been ranked as one of the major scientific challenges of this century [14]. During the past decades, a great deal of research has been devoted to identifying mechanisms by which cooperation can be maintained [15–19]. Nowak [20] summarized these mechanisms into five categories: kin selection, direct and indirect reciprocity, group selection, and spatial reciprocity.

Previous works in the literature typically assume a single-game scenario. However, players may engage in multiple game scenarios in the real-world system, and these game scenarios may interact with each other. There are two lines of research in this area. One line is from the perspective of players sequentially playing multiple correlated games [21,22]. Among them, the most important is stochastic games which provide the possibility of combining repeated games with dynamic game scenarios. The framework of stochastic games was first proposed by Shapley [23], who described the dynamics of game scenarios by introducing the concept of game states. Then a further summary and related application of the stochastic game model was provided by Solan and Vieille [24]. Evolutionary game theory was introduced into the framework of stochastic games by Hilbe *et al.* [25]. They found that the interaction between players' behaviors and scenarios enhances the propensity to cooperate. Szolnoki and Chen [26] introduced the coupling of environmental status and interactions among players. They found that this coupling can provide a significantly higher cooperation level. Su *et al.* [27] considered game transitions in structured populations, where interactions between any two neighboring players can cause changes in the game environment. They found that environmental reciprocity can promote cooperation in structured populations even if the interactions are not repeated. Given the widespread existence of information uncertainty in reality, Kleshnina *et al.* [28] investigated the effect of state uncertainty on the dynamics of cooperation in stochastic games. The results of the study show that information consistently gives an advantage to cooperation in timeout games.

The literature on multigames presented above is investigated from the perspective of players sequentially playing multiple games, and there is also a line of research from the perspective of players playing multiple concurrent games. For

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example, we may face multiple concurrent projects at work, and companies or countries may be involved in cooperation and competition in multiple areas at the same time [29,30]. With the deepening of research, scholars began to be interested in the impact of multigame scenarios on the evolution of cooperative behaviors [31–41]. Cressman *et al.* [37] initially studied the coupling of two two-person, two-strategy games, and they found that the dynamics of this coupled game can be characterized by the dynamics of a single game. Later research expanded to the coupling of multiple multiplayer games, and results showed that the dynamics of a single game is usually undetermined without considering the information of other games [38–40].

The coupling of multiple games based on complex network structures has also received a great deal of attention. Within the framework of multilayer networks, players play different games simultaneously with coplayers at different layers [42–57] and these networks are coupled by a utility function. Wang *et al.* [42] studied the public goods game based on a two-layer network. The utility function consists of the contributions of the player and the coplayer in the two-layer lattice. They found that network interdependence can promote cooperation when coordination between networks is not disturbed. Further, Su *et al.* [45] studied multigames within the framework of multilayer networks and these layers are coupled by averaging multiple payoffs. Their work showed that coupling between layers can promote cooperation even if the level of cooperation at each level is not high. The correlation between multiple games is not only reflected in the interdependence between networks but also in the edge diversity within the network. Su *et al.* [58] investigated multiplayer games on networks with edge diversity, where different types of edges denote various social ties. A player may play different games concurrently with different neighbors, based on the variety of social ties between players and their neighbors.

Recently, Donahue *et al.* [41] proposed the concept of multichannel games based on the framework of repeated games. Each channel corresponds to an infinitely repeated game and multiple channels are conducted in parallel. Correlation between these channels is established through linked strategies. They found that the correlation between games can boost players' flexibility and foster cooperation across all concurrent games. However, they assumed that the importance of multiple games was consistent and did not consider how differences in players' potential preferences for multiple games might affect the cooperation of populations. If each issue in the repeated games is considered as an objective, the payoffs of players in multiple-issue games can be represented by a payoff vector and the multiple-issue games can be defined as a multiobjective game. Inspired by this motivation, we explore the cooperation dynamics of strategies in the population from a multiobjective perspective, in which an individual's preference for each issue is described by a weight vector. Besides, we consider population heterogeneity by assigning different payoff weights to represent players who may have different preferences on the same issues. We attempted to explore the effect of players' preferences and the proportion of players with different preferences for the same issues on the evolution of cooperation. As an extension of the model, we also discuss the effects of exploration rates of seeking new strategies and stochastic strategies on the cooperative behavior of the population.

The remainder of this paper is arranged as follows. In Sec. II, we describe the multi-issue games model with strategy correlations and individual preferences in detail. In Sec. III, we show the main simulation results and the corresponding analyses. Finally, we summarize the main conclusions in Sec. IV.

II. MODEL

A. Multi-issue games between two players

In multi-issue games, each issue corresponds to an infinitely repeated prisoner's dilemma game. The players interact simultaneously on m different issues. In each round of a given game, players can choose from cooperative (C) and defective (D) actions. The payoffs in each game depend only on the player's actions in that game and are independent of the actions in the other games. The payoff matrix in issue $k(1 \leqslant k \leqslant m)$ game can be represented as

$$\begin{array}{c c} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} R_k & S_k \\ T_k & P_k \end{pmatrix} \end{array}.$$

Here, R_k denotes the reward they receive when both players cooperate, S_k denotes the sucker's payoff received by a cooperator from a defector, T_k represents the temptation payoff that a defector receives from a cooperator, and P_k is the punishment they receive when both players defect. The different orderings of T_k, R_k, P_k, and S_k characterize different social dilemma structures. The prisoner's dilemma we consider satisfies $T_k > R_k$ and $P_k > S_k$.

If $\pi_i^k(t)$ represents the payoff obtained by player i in round t of game k, then the payoff of player i in issue k is the expected payoff of the infinitely repeated game:

$$\pi_i^k = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \pi_i^k(t). \tag{1}$$

For each player, the payoff in any given round is a vector composed of multiple issues. Thus, the payoff vector for player i in round t across all issues can be represented as $[\pi_i^1(t), \pi_i^2(t), \dots, \pi_i^m(t)]$, and the payoff vector for player i across all issues is denoted as $(\pi_i^1, \pi_i^2, \dots, \pi_i^m)$.

B. Correlated strategies in multi-issue games

In repeated games, strategies are mappings from historical information (including environmental changes and the actions of coplayers) to actions [59]. Here, the correlation between different issue games is described by strategy linkage. Player i's action $a_i^k(t)$ in issue k in round t affects not only coplayer j's action $a_j^k(t+1)$ in this issue in the next round, but also the coplayer j's action $a_j^{k'}(t+1)$ in another issue $k'(k' \neq k, 1 \leqslant k' \leqslant m)$ in the next round. We focus only on reactive strategies due to the complexity of strategies, where a player's action in any round depends only on the actions of the coplayer in the previous round.

To simplify the study, we consider multi-issue games with $m = 2$ and the subsequent studies are based on the two-issue games. The reactive strategy in two-issue games can be represented by an eight-dimensional vector of the form $p = (p^1_{CC}, p^1_{CD}, p^1_{DC}, p^1_{DD}; p^2_{CC}, p^2_{CD}, p^2_{DC}, p^2_{DD})$, where $p^k_{a_1a_2}$ is the probability that a player cooperates in an issue k game when the coplayer's actions in the previous round in the two games are $a_1 \in \{C, D\}$, $a_2 \in \{C, D\}$, respectively. In particular, the two issues are uncorrelated when $p^1_{CC} = p^1_{CD}$, $p^1_{DC} = p^1_{DD}$, $p^2_{CC} = p^2_{DC}$, and $p^2_{CD} = p^2_{DD}$. A reactive strategy p can be considered deterministic (also known as pure strategy) if all entries take the value 0 or 1. It can be defined as a stochastic strategy if there exists an entry in the interval (0,1). We define a strategy as cooperative if it induces two players with that strategy to mutually cooperate when both players cooperate in the initial phase and if their actions are not affected by errors. We consider the following cooperative correlated strategies, $p = (1, 0, 0, 0; 1, 0, 0, 0)$ (denoted as TF2T) to denote the player defects in both games in the next round if the coplayer defects in either game. $p = (1, 1, 1, 0; 1, 1, 1, 0)$ (denoted as 2TFT) denotes that the player using this strategy cooperates in both games in the next round if the coplayer cooperates in one of the two games; the player defects in the next round only if the coplayer defects in both games at the same time. $p = (1, 0, 1, 0; 1, 1, 0, 0)$ (denoted as oTFT) indicates that if the coplayer defects in game 1, the player will defect in the next round in game 2, and vice versa. $p = (1, 0, 0, 1; 1, 0, 0, 1)$ (denoted as oWSLS) indicates that a player cooperates in the next round only if the coplayer's actions in both games are the same.

C. Calculation of expected payoffs and cooperation rate

The payoffs can be explicitly calculated when players adopt reactive strategies. Assuming the reactive strategies adopted by the two interacting players are $p = (p^1_{CC}, p^1_{CD}, p^1_{DC}, p^1_{DD}; p^2_{CC}, p^2_{CD}, p^2_{DC}, p^2_{DD})$ and $\tilde{p} = (\tilde{p}^1_{CC}, \tilde{p}^1_{CD}, \tilde{p}^1_{DC}, \tilde{p}^1_{DD}; \tilde{p}^2_{CC}, \tilde{p}^2_{CD}, \tilde{p}^2_{DC}, \tilde{p}^2_{DD})$, respectively we formulate the two-issue game as a Markov chain to calculate the players' payoffs, and the states of this chain are the joint action profiles of two players in a single round. Let $a = (a_1, a_2) \in \{C, D\}^2$ be the action profile of one player, and the action profile of the coplayer is $\tilde{a} = (\tilde{a}_1, \tilde{a}_2) \in \{C, D\}^2$. Then the current state of the Markov chain can be written as $\omega = (a, \tilde{a})$. Based on the current state of the Markov chain, we can infer that the probability of its next state $w' = (a', \tilde{a}')$ is

$$w_{\omega,\omega'} = \prod_{k=1}^{2} q^k_{\omega,\omega'} \tilde{q}^k_{\omega,\omega'}, \tag{2}$$

where $q^k_{\omega,\omega'}$ and $\tilde{q}^k_{\omega,\omega'}$ denote the probability of a player and coplayer moving from the current state ω to the next state ω' in game k $(1 \leqslant k \leqslant 2)$, respectively.

$$q^k_{\omega,\omega'} = \begin{cases} p^k_{\tilde{a}} & a'_k = C \\ 1 - p^k_{\tilde{a}} & a'_k = D \end{cases} \quad \tilde{q}^k_{\omega,\omega'} = \begin{cases} \tilde{p}^k_{a} & \tilde{a}'_k = C \\ 1 - \tilde{p}^k_{a} & \tilde{a}'_k = D \end{cases}. \tag{3}$$

Then we can obtain a state transition matrix $W = (w_{\omega,\omega'})$ of size 16×16. The mean value of each state in the state transition matrix converges to a unique invariant distribution $V = (v_\omega)$, where each entry v_ω gives the expected frequency of $\omega = (a, \tilde{a})$. Based on this invariant distribution, we can calculate the marginal distribution in game k:

$$v^k_{(a'_k, \tilde{a}'_k)} = \sum_{\omega} v_\omega e^k_\omega(a'_k, \tilde{a}'_k). \tag{4}$$

Here, $e^k_\omega(a'_k, \tilde{a}'_k)$ is an indicator function. When $\omega = [(a_1, a_2), (\tilde{a}_1, \tilde{a}_2)]$ satisfies $a_k = a'_k$ and $\tilde{a}_k = \tilde{a}'_k$, $e^k_\omega(a'_k, \tilde{a}'_k) = 1$. Otherwise $e^k_\omega(a'_k, \tilde{a}'_k) = 0$. The marginal distribution in game k can be represented as the vector $V^k = (v^k_{CC}, v^k_{CD}, v^k_{DC}, v^k_{DD})$.

Then the player's expected payoff in issue k game can be calculated as

$$\begin{aligned} \pi^k &= v^k_{CC} R_k + v^k_{CD} S_k + v^k_{DC} T_k + v^k_{DD} P_k, \\ \tilde{\pi}^k &= v^k_{CC} R_k + v^k_{CD} T_k + v^k_{DC} S_k + v^k_{DD} P_k, \end{aligned} \tag{5}$$

where π^k is the expected payoff of the player adopting strategy p, and $\tilde{\pi}^k$ is the expected payoff of the player interacting with him who adopts strategy $\tilde{p}$.

Similarly, the player's expected cooperation rate in issue k game can be calculated as

$$\begin{aligned} \gamma^k &= v^k_{CC} + v^k_{CD}, \\ \tilde{\gamma}^k &= v^k_{CC} + v^k_{DC}, \end{aligned} \tag{6}$$

where γ^k is the expected cooperation rate in issue k game of the player adopting strategy p, and $\tilde{\gamma}^k$ is the expected cooperation rate in issue k game of the player interacting with him who adopts strategy $\tilde{p}$.

D. Evolutionary dynamics of strategies

In a well-mixed population of size N, each player interacts with every other $N-1$ population member in multi-issue games to obtain the corresponding payoff vectors. To get each player's overall payoff in issue k in the population, we average all these payoffs in that issue. Suppose $\pi^k_{(i,j)}$ is player i's payoff when player i and player $j (i \neq j)$ interact in issue k. Player i's overall payoff $\bar{\pi}^k_i$ in issue k can be calculated as

$$\bar{\pi}^k_i = \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} \pi^k_{(i,j)}. \tag{7}$$

Then the overall payoff vector for player i across all issues is $(\bar{\pi}^1_i, \bar{\pi}^2_i)$. We assume that players have different preferences towards the two games and let the weight vector $\theta_i = (\theta^1_i, \theta^2_i)$ denote player i's preferences for different issues. We first consider the homogeneous weight vector ($\theta^1_i = \theta$ and $\theta^2_i = 1-\theta$); i.e., all players in the population have the same preferences. Players prefer game 1 when $\theta > 0.5$, players prefer game 2 when $\theta < 0.5$, and players' preferences for both games are consistent when $\theta = 0.5$. Based on the weight of a player in different issues, the player i's fitness function can be established as

$$f_i(\theta, \pi) = \sum_{k=1}^{2} \theta_i{}^k \bar{\pi}^k_i. \tag{8}$$

We consider a synchronous updating (SU) scheme to the evolutionary dynamics of the strategy. In this process, individuals only need to learn strategy but not preferences. The overall strategies update is performed after all players have played a round of the game based on the payoff information from the previous step. Players have two ways to update their strategies. One is strategy random exploration with probability μ; they can randomly select a strategy from the set of strategies and discard the previous strategy. The other is strategy imitation with probability $1-\mu$. Two players are randomly selected from the population as learner x and model y. Learner x imitates model y's strategy with probability ρ based on the fitness difference between the two of them. The imitation rule adopts Fermi's rule, with the functional form of

$$\rho = \frac{1}{1+\exp\left(-s[f_y(\theta,\pi)-f_x(\theta,\pi)]\right)}, \tag{9}$$

where $f_x(\theta,\pi)$ and $f_y(\theta,\pi)$ are the fitness of the learner x and the model y, respectively. Here, the imitation process of strategies is characterized by introducing the Pareto nondominated solutions in multiobjective decision making. If the learner x's payoff Pareto dominates the model y's, which means the payoff of learner x in any issue $1 \leqslant k \leqslant 2$ is not less than the payoff of model y ($\pi_x^k \geqslant \pi_y^k$) and there exists at least one issue $1 \leqslant l \leqslant 2$ where the inequality is strictly satisfied ($\pi_x^l > \pi_y^l$), then $f_x(\theta,\pi) \geqslant f_y(\theta,\pi)$ for any form of fitness function. According to the strategy imitation rule, imitation probability simplifies to $\frac{1}{2}$ in the limit $s \to 0$, resulting in entirely random imitation. Otherwise, learner x will imitate model y with probability if the payoff of model y is not an inferior solution with respect to learner x.

III. RESULTS AND DISCUSSION

Before the simulation begins, we first describe the definition of cooperation rate in the population. Player i's average cooperation rate $\bar{\gamma}_i^k$ in issue k in the population can be calculated as

$$\bar{\gamma}_i^k = \frac{1}{N-1}\sum_{j=1,j\neq i}^{N} \gamma_{(i,j)}^k, \tag{10}$$

where $\gamma_{(i,j)}^k$ is player i's cooperation rate when player i and player $j (i \neq j)$ interact in issue k.

Then the average cooperation rate of issue k in the population is

$$\Upsilon^k = \frac{1}{N}\sum_{i=1}^{N} \bar{\gamma}_i^k. \tag{11}$$

In our study, we use Monte Carlo simulation (MCS) to simulate the process of player interaction and strategy updating throughout a well-mixed population of size $N = 100$. To simplify the study, each game takes the form of a donation game, which is a simplified prisoner's dilemma. In the donation game, cooperation means paying a cost $c > 0$ to bring a benefit $b > c$ to the coplayer. Defection pays no cost and produces no benefit. The four payoffs are then given by $R_k = b_k - c_k$, $S_k = -c_k$, $T_k = b_k$, and $P_k = 0$. In the initial state, each player is randomly assigned a reactive strategy in the strategy space. During the evolutionary process, the population can be stabilized after about 20 000 MCSs for most parameter combinations, and the values of the following simulation results are computed by averaging the data of the last 2000 MCSs after stabilization. To eliminate the impact of accidental errors in experiments, each data result is obtained by averaging at least 30 independent experiments.

A. Cooperation dynamics with correlated strategies

Firstly, we consider that correlated strategies in the strategy space are 2TFT, oWSLS, and ALLD. We explore the dynamics of cooperative evolution when the strategy space of the initial population contains these three strategies. When these strategies interact in the two issue games, the expected payoff matrices can be calculated as

$$\begin{array}{c} \\ \text{2TFT} \\ \text{oWSLS} \\ \text{ALLD} \end{array} \begin{array}{c} \begin{array}{ccc} \text{2TFT} & \text{oWSLS} & \text{ALLD} \end{array} \\ \begin{pmatrix} \left(\frac{b_1-c_1}{2}, \frac{b_2-c_2}{2}\right) & (b_1-c_1, b_2-c_2) & (0,0) \\ (b_1-c_1, b_2-c_2) & (b_1-c_1, b_2-c_2) & (-c_1, -c_2) \\ (0,0) & (b_1, b_2) & (0,0) \end{pmatrix} \end{array}.$$

Figure 1 illustrates the evolutionary results of the three strategies in the population. In Fig. 1(a), we can observe that the average cooperation rate of the population in the two games at the initial state is about 0.5. The cooperation rate in the two games is around 0.4 when the population evolves to stability, and the change in the value of benefit b_1 has no significant effect on the cooperation level of the population. In Fig. 1(b), an increase in the number of strategy ALLD decreases the number of strategy oWSLS during the evolution of the time step from $t = 0$ to $t = 10$. Subsequently, strategy 2TFT inhibits the continued growth of strategy ALLD during the evolution of the time step from $t = 10$ to $t = 100$. This suggests that only the strategy 2TFT can resist the defective strategy ALLD. As the value of benefit b_1 increases from 1 to 5, the frequency of strategy 2TFT decreases by about 0.2 and the frequency of strategy oWSLS and strategy ALLD increase by about 0.1. This is because some players who take the strategy 2TFT are more willing to take the strategy oWSLS to pursue higher payoffs, while the strategy oWSLS is unable to resist the strategy ALLD, so it also leads to an increase in the number of strategy ALLD.

In the study above, correlated strategies in the strategy space assume that players behave consistently in both games based on the same historical behavioral information. Now we allow players to have different behaviors in different games based on the same historical behavioral information. Here we introduce game k semicooperative strategies. We define a strategy game k semicooperative if it induces two players adopting that strategy to cooperate in game k. For example, the strategy

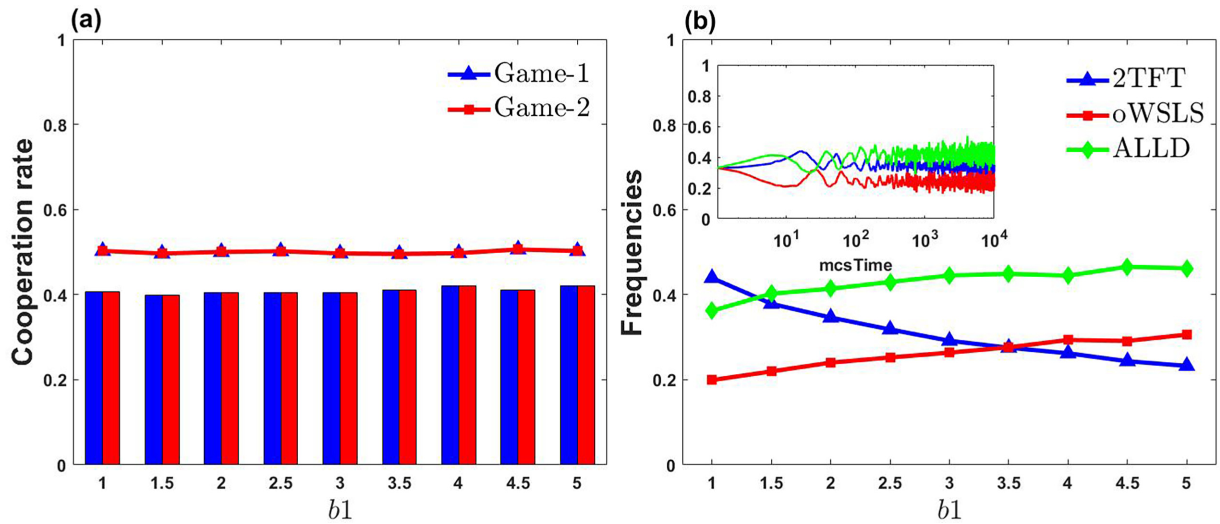

FIG. 1. The average cooperation rate in the two games of the population and frequencies of the three strategies 2TFT, oWSLS, and ALLD. In panel (a), the line shows the cooperation rate in the two games of the population at the initial state, and the cooperation rate of the two games at the steady state is illustrated by the histogram. Panel (b) shows the frequencies of different strategies when the value of benefit b_1 increases from 1 to 5. The inset shows the evolutionary process of strategies when $b_1 = 2$. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, $s = 2$, and θ=0.5.

(1, 1, 1, 0; 0, 0, 0, 0) (denoted as game-1 semi-2TFT) indicates that the player always defects in game 2, and that the player only defects in game 1 when the coplayer defects in both games. The strategy (1, 0, 0, 1; 0, 0, 0, 0) (denoted as game-1 semi-oWSLS) indicates that the player always defects in game 2 and that the player only defects in game 1 when the coplayer's behavior is inconsistent between the two games. The strategy (0, 0, 0, 0; 1, 1, 1, 0) (denoted as game-2 semi-2TFT) indicates that the player always defects in game 1, and the player defects in game 2 only when the coplayer defects in both games. The strategy (0, 0, 0, 0; 1, 0, 0, 1) (denoted game-2 semi-oWSLS) indicates that the player always defects in game 1, and the player defects in game 2 only when the coplayer's behavior is inconsistent between the two games. Then these four semicooperative strategies and the previously mentioned correlated strategies 2TFT, oWSLS are classified into two profiles: C1(2TFT, game-1 semi-2TFT, game-2 semi-2TFT) and C2(oWSLS, game-1 semi-oWSLS, game-2 semi-oWSLS). When these strategies interact in the two issue games, the expected payoff matrices can be calculated as

$$\begin{array}{cc} \text{C1} & \begin{array}{ccc} \text{2TFT} & \text{Game-1 semi-2TFT} & \text{Game-2 semi-2TFT} \end{array} \\ \begin{array}{c} \text{2TFT} \\ \text{Game-1 semi-2TFT} \\ \text{Game-2 semi-2TFT} \end{array} & \begin{pmatrix} \left(\frac{b_1-c_1}{2}, \frac{b_2-c_2}{2}\right) & \left(-\frac{c_1}{2}, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1-c_1}{2}, -\frac{c_2}{2}\right) \\ \left(\frac{b_1}{2}, \frac{b_2-c_2}{2}\right) & \left(0, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1}{2}, -\frac{c_2}{2}\right) \\ \left(\frac{b_1-c_1}{2}, \frac{b_2}{2}\right) & \left(-\frac{c_1}{2}, \frac{b_2}{2}\right) & \left(\frac{b_1-c_1}{2}\right), 0) \end{pmatrix} \end{array},$$

$$\begin{array}{cc} \text{C2} & \begin{array}{ccc} \text{oWSLS} & \text{Game-1 semi-oWSLS} & \text{Game-2 semi-oWSLS} \end{array} \\ \begin{array}{c} \text{oWSLS} \\ \text{Game-1 semi-oWSLS} \\ \text{Game-2 semi-oWSLS} \end{array} & \begin{pmatrix} (b_1-c_1, b_2-c_2) & (0, b_2) & (b_1, 0) \\ (0, -c_2) & \left(0, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1}{2}, \frac{-c_2}{2}\right) \\ (-c_1, 0) & \left(\frac{-c_1}{2}, \frac{b_2}{2}\right) & \left(\frac{b_1-c_1}{2}, 0\right) \end{pmatrix} \end{array}.$$

Then we explored the dynamics of cooperation when the strategy spaces of the initial population are profile C1 and profile C2, respectively. As shown in Fig. 2(a-1), the population is at a low cooperation level in both games when the strategy space is profile C1. Specifically, the cooperation rate in game 1 is negatively correlated with benefit b_1, while the cooperation rate in game 2 is positively correlated with benefit b_1. To further explore this reason, we study the frequencies of strategies in the population. As shown in Fig. 2(a-2), we find that the strategy oTFT has died out, the strategy game-1 semi-2TFT is negatively correlated with benefit b_1, and the strategy game-2 semi-2TFT is positively correlated with benefit b_1 when the population is stabilized. This is because as the benefit b_1 gradually exceeds the benefit b_2, players are more inclined to defect in game 1 in pursuit of higher payoffs. Players adopting strategy game-2 semi-2TFT choose to defect in game 1 and tend to cooperate in game 2, whereas players adopting strategy game-1 semi-2TFT have a high degree of tolerance in game 1 and choose to defect in game

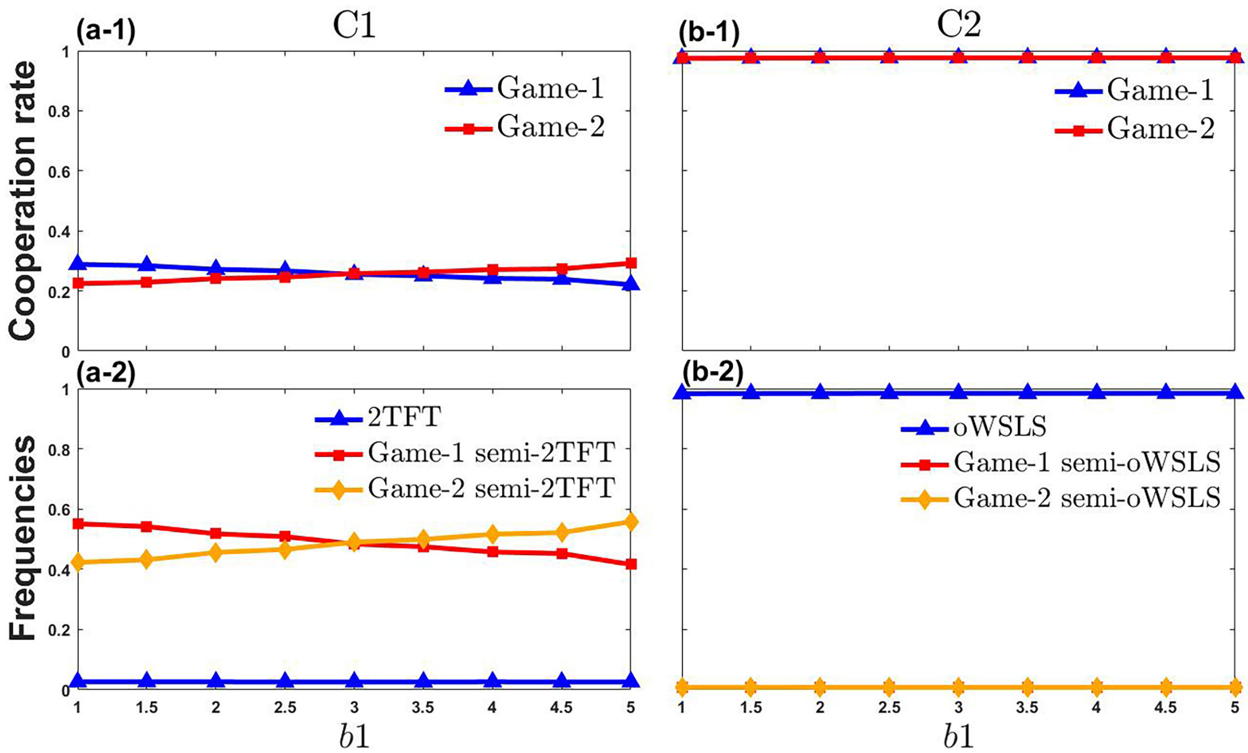

FIG. 2. The cooperation rate in both games and frequencies of strategies with the benefit b_1 under different strategy profiles. (a) Profile C1; (b) profile C2; (1) the cooperation rate; (2) frequencies of strategies. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, $s = 2$, and θ=0.5.

1 only if their coplayer defects in both games. Therefore, the number of players who choose to adopt strategy game-2 semi-2TFT increases gradually as the benefit b_1 increases. As shown in Fig. 2(b-1), when the strategy space is profile C2, we find that the population reaches a state of full cooperation in both games, regardless of the variation of benefit b_1. This reason can be found in Fig. 2(b-2); strategy game-1 semi-oWSLS and strategy game-2 semi-oWSLS are extinct, and only strategy oWSLS exists in the population when the population reaches a steady state. This is because players who take the strategy oWSLS defect strictly when faced with coplayers whose behavior is inconsistent.

We further expand the strategy space by introducing the strategy oWSLS from profile C2 into profile C1. Then the strategy space consists of 2TFT, game-1 semi-2TFT, game-2 semi-2TFT, and oWSLS. When these strategies interact in the two issue games, the expected payoff matrices can be calculated as

$$\begin{array}{l} \\ \text{2TFT} \\ \text{Game-1 semi-2TFT} \\ \text{Game-2 semi-2TFT} \\ \text{oWSLS} \end{array}
\begin{array}{c} \begin{array}{cccc} \text{2TFT} & \text{Game-1 semi-2TFT} & \text{Game-2 semi-2TFT} & \text{oWSLS} \end{array} \\
\begin{pmatrix}
\left(\frac{b_1-c_1}{2}, \frac{b_2-c_2}{2}\right) & \left(-\frac{c_1}{2}, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1-c_1}{2}, -\frac{c_2}{2}\right) & (b_1-c_1, b_2-c_2) \\
\left(\frac{b_1}{2}, \frac{b_2-c_2}{2}\right) & \left(0, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1}{2}, -\frac{c_2}{2}\right) & \left(\frac{b_1}{2}, \frac{b_2-c_2}{2}\right) \\
\left(\frac{b_1-c_1}{2}, \frac{b_2}{2}\right) & \left(-\frac{c_1}{2}, \frac{b_2}{2}\right) & \left(\frac{b_1-c_1}{2}, 0\right) & \left(\frac{b_1-c_1}{2}, \frac{b_2}{2}\right) \\
(b_1-c_1, b_2-c_2) & \left(-\frac{c_1}{2}, \frac{b_2-c_2}{2}\right) & \left(\frac{b_1-c_1}{2}, -\frac{c_2}{2}\right) & (b_1-c_1, b_2-c_2)
\end{pmatrix} \end{array}.$$

To investigate how the newly introduced strategy would affect the population's evolutionary dynamics, Fig. 3(a) illustrates the evolution results of cooperation when the population reaches a steady state. We find that the introduction of strategy oWSLS can significantly promote cooperation in both games. Specifically, the cooperation rate in both games gradually increases as the value of the benefit b_1 increases from 1 to 2. The two games almost reach a full cooperation state when benefit $b_1 = 2$. To further explore this reason, we studied the frequencies of strategies in the population. As shown in Fig. 3(b), a large benefit b_1 is beneficial for the survival of strategy oWSLS. As the benefit b_1 increases from 1 to 2, the frequencies of strategy game-1 semi-2TFT and strategy game-2 semi-2TFT rapidly decline and strategy oWSLS rapidly increases. When benefit $b_1 = 2$, the strategy oWSLS occupies almost the entire population.

B. Homogeneous population with the same preferences

In the above study, players place equal importance on both games. Next we explore the effect of variation in game

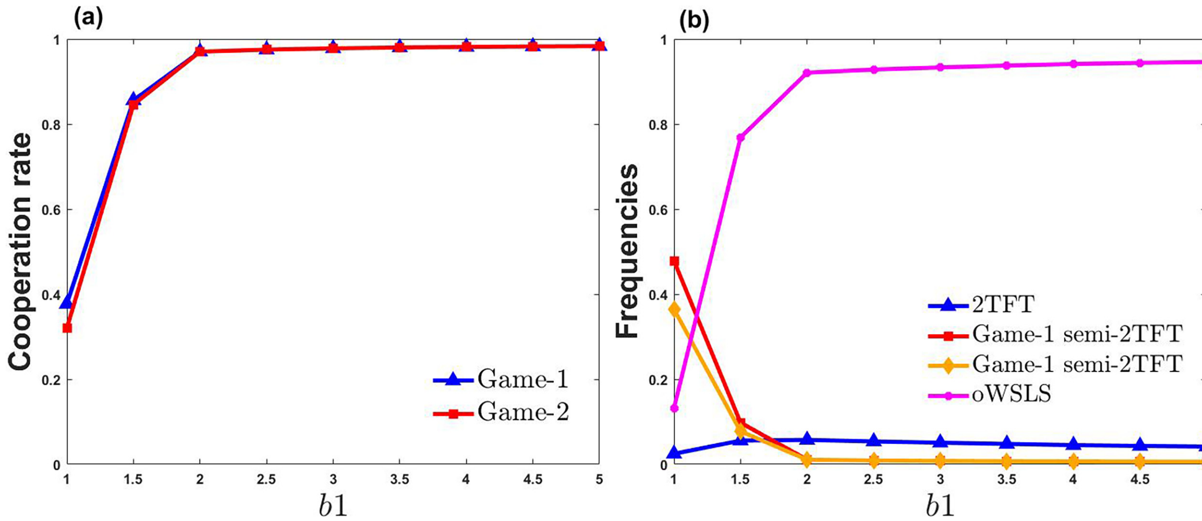

FIG. 3. The cooperation rate and frequencies of strategies under different benefits b_1. Panel (a) shows the cooperation rate in the two games increases in both games as benefits b_1 increase. Panel (b) shows the frequency of strategy oWSLS is positively correlated with benefit b_1; strategy game-1 semi-2TFT and strategy game-2 semi-2TFT are negatively correlated with benefit b_1. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, $s = 2$, and $\theta = 0.5$.

preferences on the level of population cooperation by varying the value of the payoff weights θ. In contrast to the work of Donahue *et al.* [41], we have two main results when considering homogeneous preferences. One is that players are more inclined to defect in the more preferred game 1. The other is the smaller the difference in preference between the two games, the broader the parameter area that a high level of cooperation can survive. Cooperative evolution results in both games are shown in Fig. 4. The first result can be seen in the upper left corner of Figs. 4(a) and 4(b); under small benefit b_1, the more players prefer a given game, the lower the cooperation in that game. The cooperation rate of game 1 is lower than 0.2, while the cooperation rate of game 2 stays around 0.5. In the bottom left corner of Figs. 4(a) and 4(b), we find that the cooperation rate of game 1 is higher than 0.6, while the cooperation rate of game 2 is lower than 0.5. Players are more inclined to defect in game 2. As for the second result, we can find that as θ increases from 0 to 0.5, the critical value of b_1 for full cooperation decreases to about 2. As θ continues to increase from 0.5 to 1, the critical value of b_1 for full cooperation increases to around 3.5. When $\theta = 0.5$, the critical value of b_1 required for full cooperation is minimized.

To explain this result, Fig. 5 shows the frequencies of strategies with the benefit b_1 for different payoff weights θ. As Fig. 5(a) depicts, when $\theta = 0.1$ and under small benefit b_1, the majority of players in the population take the strategy

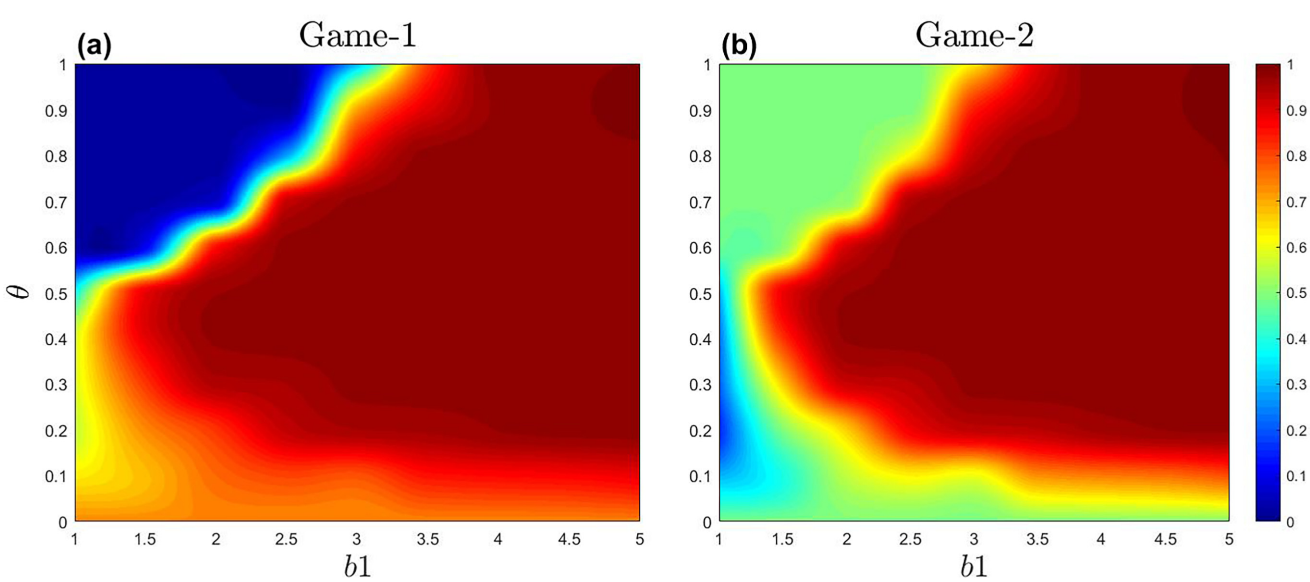

FIG. 4. Color-coded cooperation rate in both games in dependence on benefit b_1 and payoff weights θ. (a) the cooperation rate in game 1; (b) the cooperation rate in game 2. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, and $s = 2$.

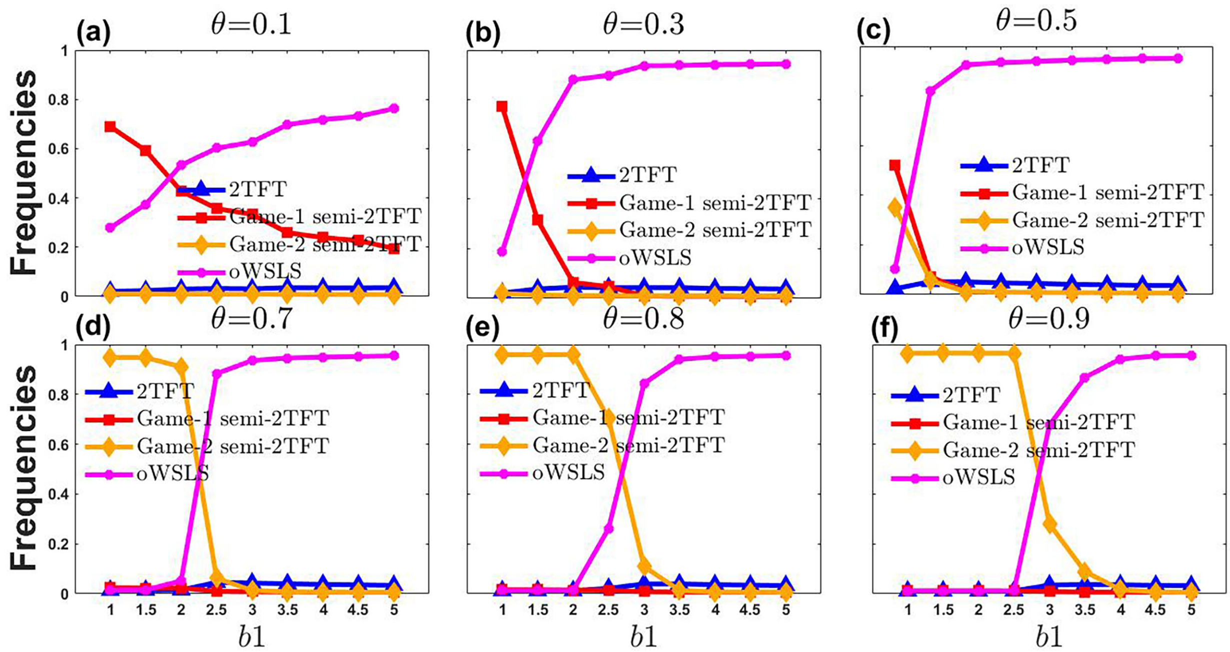

FIG. 5. The frequencies of strategies with the benefit b_1 under different payoff weights θ. In panels (a–c), an increase in θ facilitates the strategy oWSLS to occupy populations over a wider range of parameters and reduce the survival range of strategy game-1 semi-2TFT. In panels (d–f), continued increase of θ reduce the survival range of strategy oWSLS and facilitates the strategy Game-2 semi-2TFT to occupy populations over a wider range of parameters. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, and $s = 2$.

game-1 semi-2TFT, while the number of players adopting oWSLS gradually increases as b_1 increases. This is because the payoff weights between the two games differ significantly; players can get more payoff in game 2, while the payoffs players can get in game 1 are very small. Regardless of whether players choose to cooperate or defect in game 1, the influence of that game on the players is negligible. This provides favorable conditions for players to choose defection in game 2 to pursue high payoffs without fearing retaliation from opponents in game 1. As b_1 increases, strategy oWSLS can get more payoffs during the strategy interaction. This motivates players to choose the oWSLS strategy and maintain cooperation within the population. As shown in Figs. 5(a)5(c), as the difference in payoff weights between the two games gradually decreases, the payoffs players can get in game 2 also gradually decrease, which undoubtedly weakens the motivation for players to defect in that game. The critical value of b_1 required to motivate players to choose oWSLS also gradually decreases and expands the parameter range where cooperation can be maintained. When the payoff weights of the two games are equal, the optimal condition to sustain cooperation to the maximum extent is achieved. A similar phenomenon can be seen in Figs. 5(d)–5(f).

C. Heterogeneous population with different preferences

In general, heterogeneous populations can offer a better condition for cooperation. For example, Szolnoki and Szabó [60] introduced heterogeneous teaching activities, where some players are better at spreading their strategy, leading to higher cooperation levels. Perc and Szolnoki [61] introduced heterogeneity through social diversity; they found that differences in social status or wealth help enhance cooperation. Here, we consider the heterogeneous preferences of individuals in the population which allow different players to have different preferences. Specifically, we further divide the population into two groups of players: one group prefers issue 1 (where $0.5 < \theta_1 \leqslant 1$), with a proportion denoted as α; the other group prefers issue 2 (where $0 \leqslant \theta_2 < 0.5$ and $\theta_1 + \theta_2 = 1$), with a proportion of $1-\alpha$. The larger the value of α, the more players in the population prefer game 1. The case of $\alpha = 1$ indicates everyone in the population prefers game 1. The other extreme, $\alpha = 0$, means that everyone in the population prefers game 2.

In contrast to the work of Donahue *et al.* [41], we find that there exists an optimal proportion of players with different preferences under which the cooperation rate can reach its highest level in the population when considering heterogeneous preferences. We mainly observe two evolutionary results in Fig. 6(a-1). As the proportion α of the population preferring game 1 increases, the cooperation in the two games first increases and then decreases, and the optimal proportion that contributes to cooperation is around $\alpha = 0.5$. The other result is that cooperation in game 1 is higher than that in game 2 when $\alpha < 0.5$, the cooperation in the two games is equal when $\alpha = 0.5$, and the cooperation in game 1 is lower than that in game 2 when $\alpha > 0.5$. The reasons for these two results can be seen in Fig. 6(a-2). In extreme cases (i.e., $\alpha = 0$ and $\alpha = 1$), the population is homogeneous. As α increases, the degree of heterogeneity in the population first increases and then decreases. Correspondingly, the cooperation rate in the population also first increases and then decreases. As α increases from 0 to 0.5, although players who prefer game 2 still constitute the majority of the population, their proportion

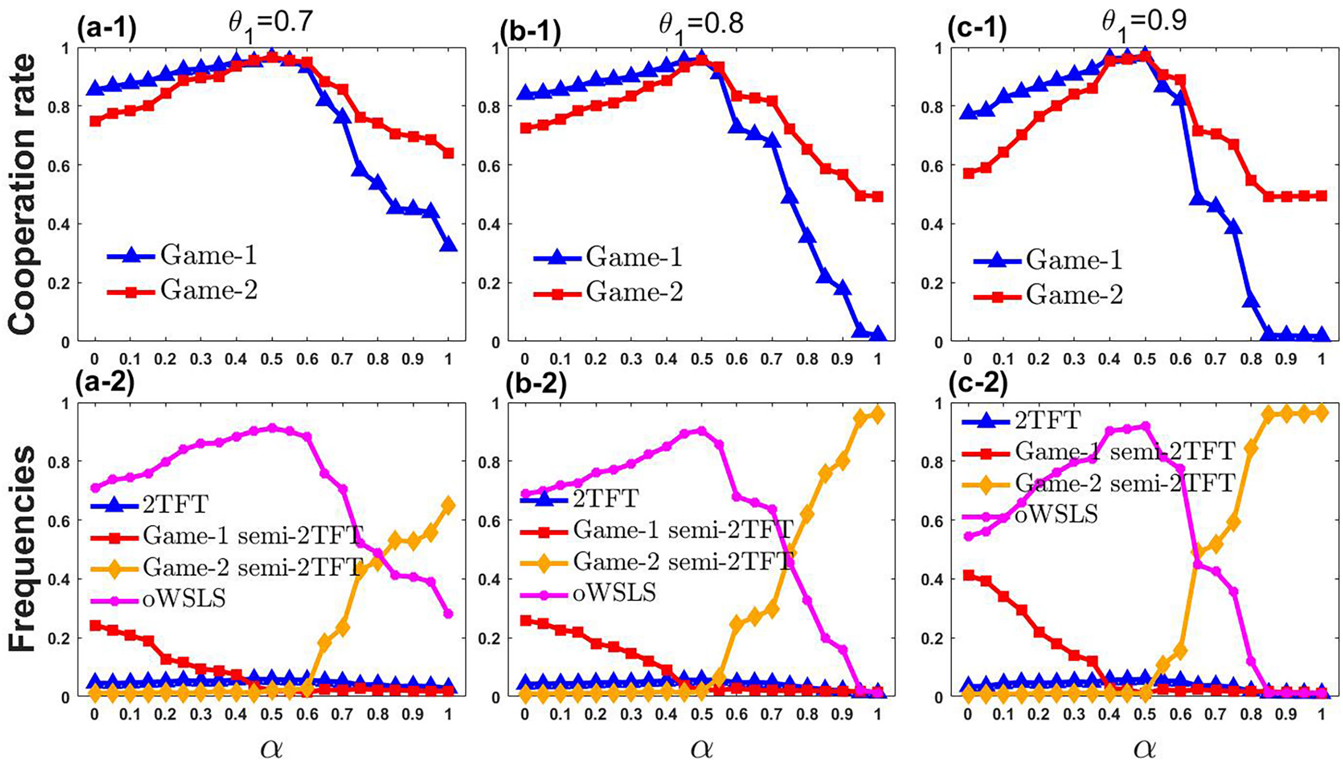

FIG. 6. The cooperation rate and frequencies of strategies with the proportion α of the population favoring game 1 under different payoff weights. (a) $\theta_1 = 0.7$; (b) $\theta_1 = 0.8$; (c) $\theta_1 = 0.9$; (1) the cooperation rate; (2) the frequencies of strategies. Parameters: $b_1 = 2$, $b_2 = 3$, $c_1 = c_2 = 1$, and $s = 2$.

is gradually decreasing. As a result, the proportion of game-1 semi-2TFT in the population is decreasing and oWSLS is gradually increasing. The existence of the strategy oWSLS facilitates cooperation in both games in the population, whereas the strategy game-1 semi-2TFT only promotes cooperation in game 1. This leads to the fact that although cooperation increases in both games, cooperation in game 1 is always higher than cooperation in game 2. When $\alpha = 0.5$, the only two strategies in the population are oWSLS and 2TFT. Players who choose these two strategies exhibit the same behavior in both games. At the same time, the number of players who choose to take the strategy oWSLS reaches the highest, so the level of cooperation is the same and maximized in both games. When α continues to increase from 0.5 to 1, players

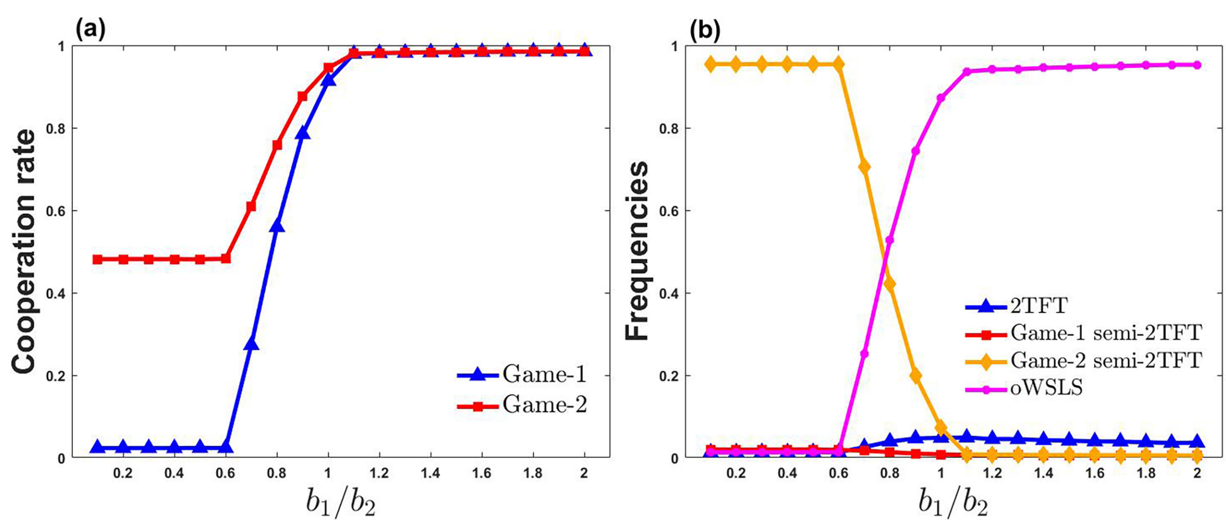

FIG. 7. The cooperation rate and frequencies of strategies with relative benefit b_1/b_2. Panel (a) shows the cooperation rate in the two games increases with the increase of b_1/b_2. Panel (b) indicates the frequency of strategy oWSLS increases and the frequency of strategy game-2 semi-2TFT decreases as b_1/b_2 increases. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, $s = 2$, $\theta_1 = 0.9$, and $\alpha = 0.8$.

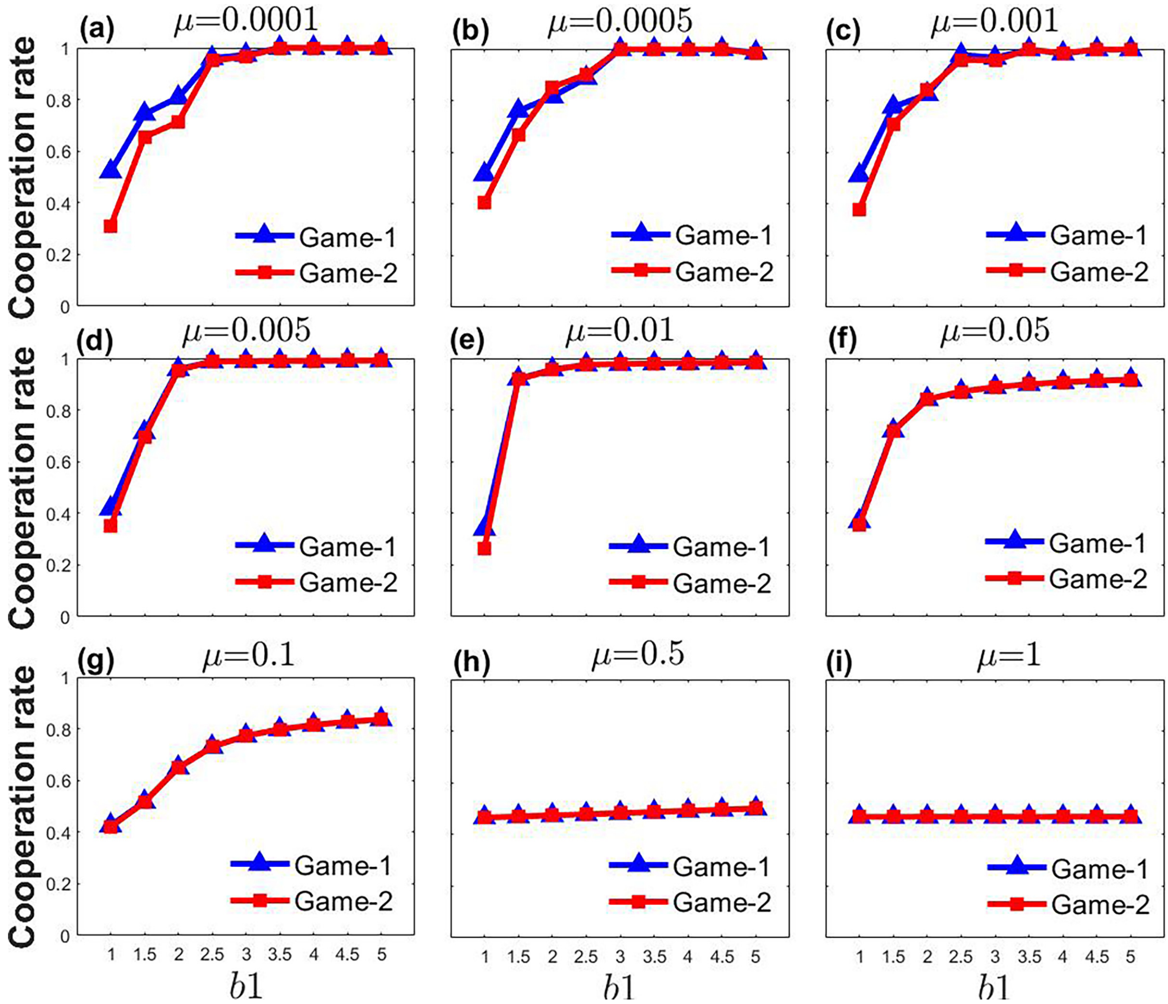

FIG. 8. The cooperation rate under different exploration rates μ. The cooperation rate in the two games gradually increases and then decreases as the mutation rate μ increases. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, $s = 2$, and $\theta = 0.5$.

who prefer game 1 constitute the majority of the population, and their proportion is gradually increasing. Correspondingly, the proportion of game-2 semi-2TFT in the population is also increasing and oWSLS is decreasing. The emergence of the strategy game-2 semi-2TFT promotes cooperation in game 2, so the cooperation in game 2 is higher than the cooperation in game 1. A similar phenomenon can be observed in Figs. 6(b) and 6(c). Under the same conditions, an increase in θ will further increase the payoff difference between the two games, making the promotion effect of heterogeneity on the population cooperation rate more significant.

In the above, we fixed the relative benefit b_1/b_2. Next, we further explore the effect of b_1/b_2 on the evolution of cooperation in Fig. 7. In Fig. 7(a), we find that an increase in b_1/b_2 promotes cooperation in both games. Specifically, cooperation in both games begins to increase at $b_1/b_2 = 0.5$, and the two games reach full cooperation at $b_1/b_2 = 0.9$. In Fig. 7(b), we can observe that players in the population almost adopt the strategy game-2 semi 2TFT when $b_1/b_2 \leqslant 0.5$, which is because, in this parameter range, players are more inclined to defect in game 1. As b_1/b_2 increases, more players will tend to adopt the strategy oWSLS, and the strategy oWSLS occupies almost the entire population at $b_1/b_2 = 0.9$.

D. Model extensions and robustness test

Figure 8 presents the details of how exploration rates μ influence the level of cooperation in the two games. As shown in Figs. 8(a)–8(e), an increase in the rate of exploration enhances the level of cooperation in the two games of the population and results in a smaller value of benefit b_1 required for the population to reach a fully cooperative state. In particular, the exploration rate that can maximize cooperative emergence in both games is μ=0.01. In Figs. 8(f)–8(i), continued increases in the rate of exploration inhibit the level of cooperation in the two games of the population. Besides, we find that the difference in the level of cooperation between the two games gradually diminishes as the exploration rate increases. In particular, when the exploration rate $\mu = 1$, the two games have the same level of cooperation and are not affected by benefits b_1. The reason for this is that, as the exploration rate increases, players randomly select a strategy from the strategy space during strategy updating with a larger probability and engage in payoff-dependent strategy imitation with a smaller probability. When the exploration rate $\mu = 1$, players only randomly select one strategy from the strategy space in the process of strategy updating.

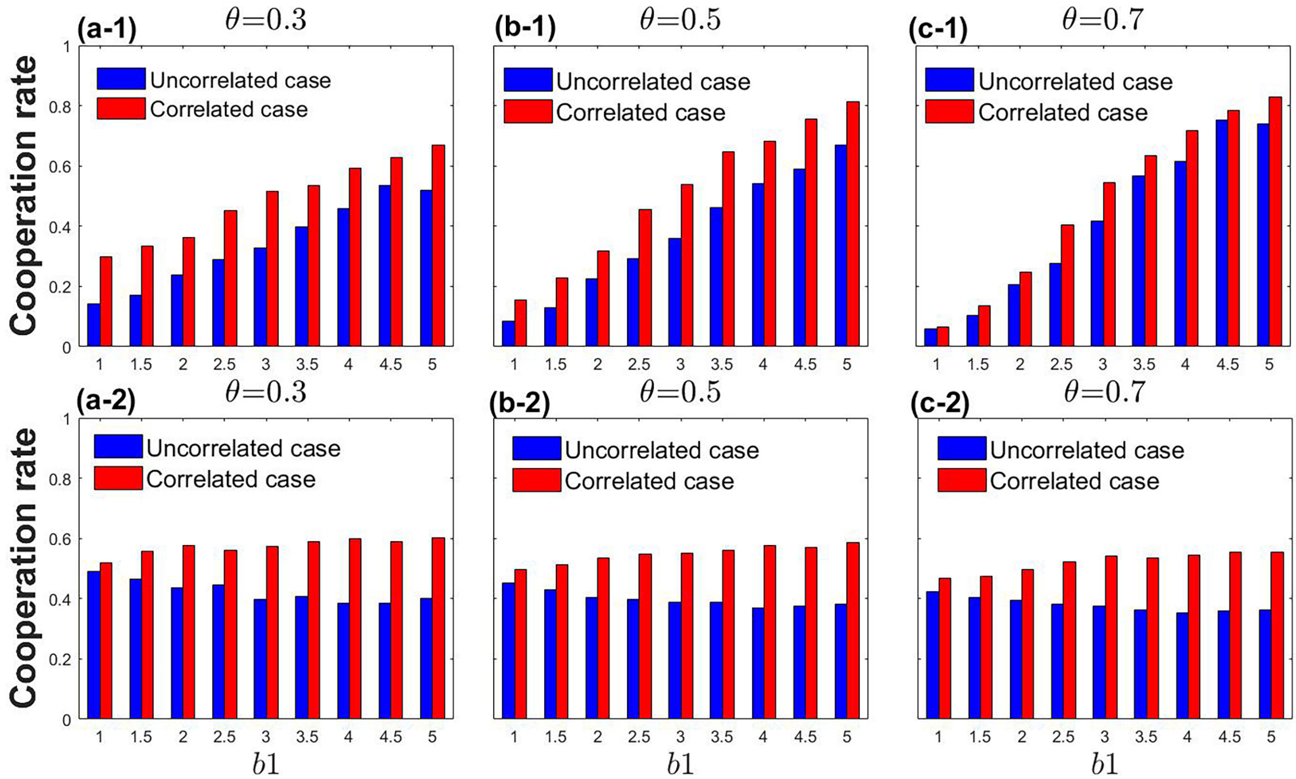

FIG. 9. The cooperation rate in both games with the benefit b_1 under different payoff weights θ. (a) $\theta = 0.3$; (b) $\theta = 0.5$; (c) $\theta = 0.7$. (1) The cooperation rate in game 1; (2) the cooperation rate in game 1. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, and $s = 2$.

We further expand the study by considering that the strategy space consists of stochastic strategies. A strategy can be defined as a stochastic strategy if each entry in the eight-dimensional vector of the strategy is uniformly sampled in the interval (0,1). We assume the limit of rare exploration $\mu \to 0$ for the strategy update process, which can simplify the calculation of the evolutionary dynamics [62–64]. We conduct 200 simulations and record the cooperation rate of each player at the end of each simulation. Figure 9 shows the evolutionary results of the cooperation of correlated stochastic strategies and uncorrelated stochastic strategies. Compared to the uncorrelated case, the correlated case can significantly promote cooperation in both games regardless of which game players prefer. As shown in Fig. 9(a), the correlation between games can significantly enhance cooperation in the two games when $\theta = 0.3$. In Figs. 9(b) and 9(c), this enhancement in the two games can also be seen when $\theta = 0.5$ and $\theta = 0.7$, respectively. Besides, in Fig. 9(a-1), we can also find that the cooperation rate in game 1 increases as benefits b_1 increase under correlated strategies and uncorrelated strategies. In Fig. 9(a-2), the cooperation rate in game 2 decreases as benefits b_1 increase under uncorrelated strategies, and the cooperation rate in game 2 increases as b_1 increases under correlated strategies. Comparing Figs. 9(a-1), 9(b-1), and 9(c-1), we further find that an increase in θ can amplify the effect of b_1 on cooperation in game 1, while in Figs. 9(a-2), 9(b-2), and 9(c-2), the change in θ does not have a significant effect on the cooperation rate in game 2.

Each entry of the stochastic strategy is randomly generated between 0 and 1. The definitions of cooperative and defective strategies for deterministic strategies no longer apply to stochastic strategies. To quantify the frequencies of different strategy categories in the evolutionary simulation, we define a stochastic strategy as approximately cooperative if it induces two players with that strategy to mutually cooperate with a probability of at least 0.8 [41]. Similarly, a stochastic strategy is defined as approximately noncooperative if the cooperation rate is below 0.2. We conduct 200 simulations and record the cooperation rate of each player at the end of each simulation. Then we distinguish four categories of strategies according to the players who may cooperate in both games (AC), cooperate in one game and defect in the other (C1 or C2), and defect in both games (AD). Figure 10 shows the frequencies of the four categories of strategies with the benefit b_1 for different payoff weights θ. As Fig. 10(a) depicts, when $\theta = 0.3$, the frequency of strategy AC and strategy C1 gradually increase with the increase of benefit b_1, and the frequency of strategy C2 and strategy AD gradually decrease with the increase of benefit b_1. Both strategies AC and C1 can promote cooperation in game 1, which explains why an increase in b_1 can promote cooperation to a greater extent in game 1 than in game 2. The increase in strategies AC and C1 provides a double boost to cooperation in game 1, while the decrease in strategy C2 diminishes the boost to cooperation in game 2 provided by strategy AC. Comparing Figs. 10(a)–10(c), we further find that the frequency of strategy C1 gradually increases and

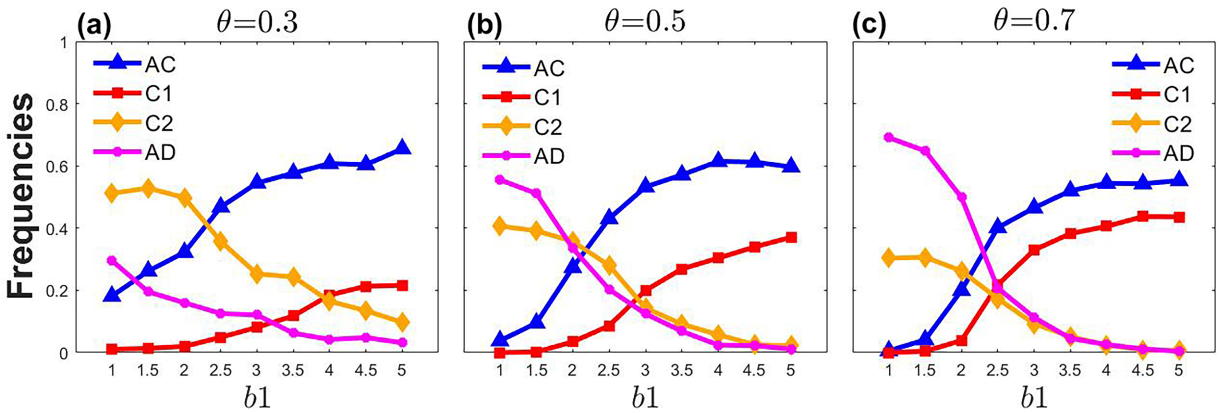

FIG. 10. The frequencies of strategies with different benefits b_1 and payoff weighs θ. The frequencies of AC and C1 are positively correlated with the benefit b_1, and the frequencies of C2 and AD are negatively correlated with the benefit b_1. The frequency of C1 gradually increases while the frequency of C2 gradually decreases with the increase of payoff weight θ. Parameters: $b_2 = 3$, $c_1 = c_2 = 1$, and $s = 2$.

the frequency of C2 gradually decreases as θ increases. This explains why an increase in θ amplifies the effect of b_1 on cooperation in game 1, while it does not have a significant effect on the cooperation rate in game 2. This reasoning is similar to the above.

For all previous evolutionary simulations, we fixed the selection intensity $s = 2$. However, the selection intensity plays an important role in determining the impact of the game on reproductive success [65]. Here Fig. 11 shows that we obtain similar results when we vary the selection intensity s. As shown in Fig. 11(a), under different selection intensities s, the decrease in the difference in preferences between the two games can still increase the parameter area that a high level of cooperation can survive. As shown in Fig. 11(b), under different selection intensities s, the optimal proportion of players with different preferences under which the cooperation rate can reach its highest level in the population remains around 0.5.

IV. CONCLUSION

In this paper, we study a multi-issue game model from a multiobjective and correlated strategy perspective. In this model, multiple issue games are played simultaneously and each issue is represented by an infinitely repeated prisoner's dilemma game. The correlations between different issues are established through both strategies and payoffs. The correlated strategy means that a player's action in an issue not only depends on the historical behavioral information in this issue but also on the historical behavioral information of other issues. Preferences for issues are measured by a weight vector. We also consider population heterogeneity in the model by assigning different payoff weights to represent players who may have different preferences on the same issues.

Our results are based on the model of two issues. Firstly, we investigate the evolutionary results of cooperation under different strategy spaces. We find that the introduction of strategy oWSLS can promote the cooperation of the population

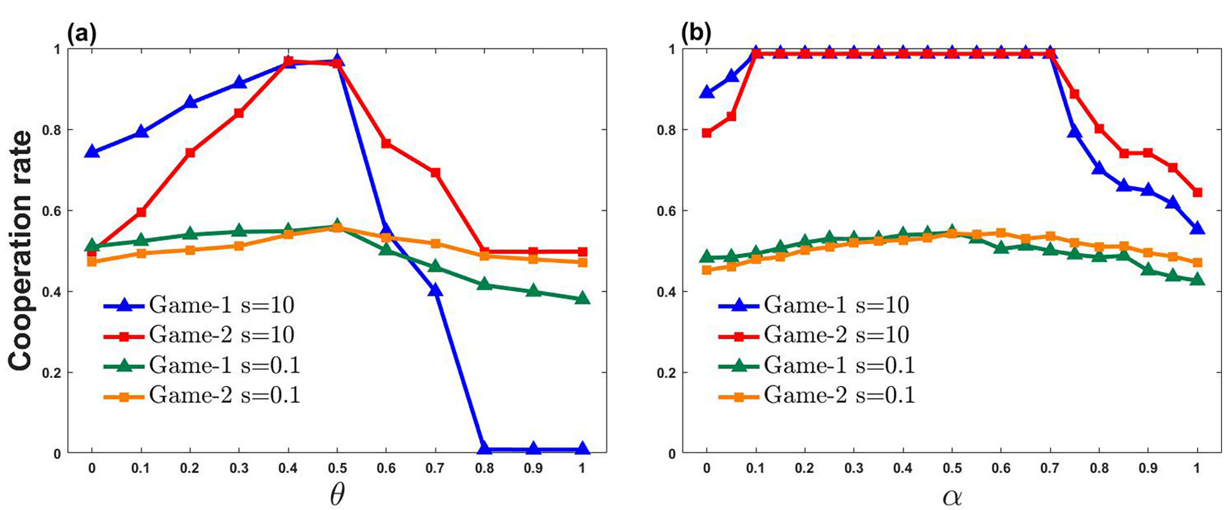

FIG. 11. The cooperation rate in both games under different selection intensities s. (a) The effect of different game preferences θ on cooperation rate under homogeneous preferences when $s = 10$, 0.1, respectively. (b) The effect of different proportions α on cooperation under heterogeneous populations when $s = 10$, 0.1, respectively. Parameters: $b_1 = 2$, $b_2 = 3$, $c_1 = c_2 = 1$, and $\theta_1 = 0.7$.

and can be the dominant strategy in the population under the large benefit of game 1. Then we find that, under the small benefit of game 1, players are more inclined to defect in a game if that game is preferred by players. We also find that the smaller the difference in preferences between the two games, the broader the parameter area that a high level of cooperation can survive. Specifically, as the payoff weight of game 1 increases, the value of the benefit of game 1 required for full cooperation decreases and then increases. When the payoff weights of both games are the same, the value of the benefit of game 1 required for full cooperation is minimized. Besides, under the condition of heterogeneous payoff weight, we further find an optimal proportion of players with different preferences for the same issues that can make a peak of cooperation in both games in the population. Finally, we further extend the study by varying the mutation rate and by considering the strategy space consisting of stochastic strategies. We find that an increased mutation rate first promotes and then inhibits the level of cooperation in the population. Compared to the uncorrelated stochastic strategies, the correlated stochastic strategies can significantly promote cooperation in both issues regardless of which issue players prefer. These results extend our understanding of the evolution of cooperation in correlated multi-issue social dilemmas. However, our study is limited to the strategy space of reactive strategies, and the model can be extended to a larger strategy space, such as memory-one strategies or even memory-n strategies. In addition, the study of correlated multi-issue games in a structured population deserves further exploration.

ACKNOWLEDGMENTS

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