Fairness emergence from zero-intelligence agents

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(Received 10 September 2009; revised manuscript received 11 November 2009; published 11 February 2010)

Fairness plays a key role in explaining the emergence and maintenance of cooperation. Opponent-oriented social utility models were often proposed to explain the origins of fairness preferences in which agents take into account not only their own outcomes but are also concerned with the outcomes of their opponents. Here, we propose a payoff-oriented mechanism in which agents update their beliefs only based on the payoff signals of the previous ultimatum game, regardless of the behaviors and outcomes of the opponents themselves. Employing adaptive ultimatum game, we show that (1) fairness behaviors can emerge out even under such minimalist assumptions, provided that agents are capable of responding to their payoff signals, (2) the average game payoff per agent per round decreases with the increasing discrepancy rate between the average giving rate and the average asking rate, and (3) the belief update process will lead to 50%-50% fair split provided that there is no mutation in the evolutionary dynamics.

DOI: 10.1103/PhysRevE.81.026104 PACS number(s): 89.65.Ef, 87.23.Ge, 02.50.Le, 87.10.Rt

Understanding the evolution of cooperative behavior is one of the greatest challenges in the modern biological and social sciences. Fairness plays a key role in explaining the emergence and maintenance of cooperation in evolving populations. In order to punish unfair behaviors, humans are even willing to forego material payoffs [1]. Such fairness and other-regarding preferences have been widely studied by using the ultimatum game [2]. In the standard version of the ultimatum game, two players are given the opportunity to split a sum of money. They are assigned the role of either proposer or responder. The proposer makes an offer on how to divide this money and the responder can then accept or reject the proposer's offer. If it is accepted, the money is split as proposed, whereas if it is rejected, then neither player receives anything. The canonical economic model of pure self-interest predicts that the proposer will offer the smallest share possible and that the responder will accept any positive offer because the alternative is a zero payoff. However, ultimatum game literature indicates that, irrespective of the monetary sum, proposers typically make offers of 40% to 50% and responders routinely reject offers under 20% [3]. Furthermore, this kind of inequity aversion may not be uniquely human quality. Once being put under conditions similar to those of humans, animals would also behave like humans, if they are able to grasp the fundamental aspects of these conditions. For example, brown capuchin monkey responded negatively to unequal reward distribution in exchanges with a human experimenter [4]. There is a voluminous literature discussing the cultural, social, and genetically evolutionary origins of the observed fairness preferences, in which all players are capable of comparing their own efforts and payoffs with those of others [5–7]. However, remembering opponents' payoffs or reasoning out a better strategy is a difficult task for most nonhumans with extremely low intelligence. Therefore, we need to reduce the complexity of the rules, which an individual, animal, or human, must be able to grasp in order to show fairness behavior in the ultimatum game. This paper develops an adaptive ultimatum game model in which agents are only required to react adaptively to their own payoff signals of the previous ultimatum game. Unlike those opponent-oriented models, agents are not required to have remembering or reasoning capability. Based on computer simulations, the results show that fairness behaviors can always emerge from zero intelligence agents. The ultimatum game will even reach at 50%-50% fair split if there is no mutation in the evolutionary dynamics.

To show how our payoff-oriented model can lead to the emergence of fairness behaviors, we introduced the adaptive ultimatum game and studied it from the perspective of evolutionary game theory. Different from the published literature, we shift our focus on fairness behavior rather than on fairness sense. The opponent-oriented concept of fairness sense is related to player's subjective understanding of the equity of the situation. Such subjective approaches might work in studying humans, but are impossible in studying nonhumans. Fairness behavior method relies on the information provided by players' behavioral reactions to inequitable situations. It is a more general concept and can be applied to study both humans and nonhumans [8]. Similar to the adaptive dynamics framework to describe evolutionary ultimatum game in Refs. [9,10], fairness behaviors can be characterized by agents' willingness to give to and anticipation to receive from their opponents. For a given monetary sum, the agent acting as proposer will offer its own *giving rate* p of the total money and the agent acting as responder will reject any offer smaller than its own *asking rate* q of the total money. Without loss generality, we set the total money to 1. The values of p and q, called as a player's strategy in Ref. [9], can represent agents' internal beliefs about how to respond to external payoff signals. Evidently, we can observe more fairness behaviors when p and q are more close to 0.5. In our adaptive ultimatum game, we assume agents with little intelligence so that we can uncover the evolutionary mechanism of fairness from the view of population dynamics of zero intelligence agents [11]. In the evolutionary process of our adaptive ultimatum game, each agent makes offer or responds to other agent's offer only based on its internal belief value p or q. Agents do not purposefully make any strategic offers that are less likely to be refused. They also do not intentionally punish their opponents. For each ultimatum game, if the re-

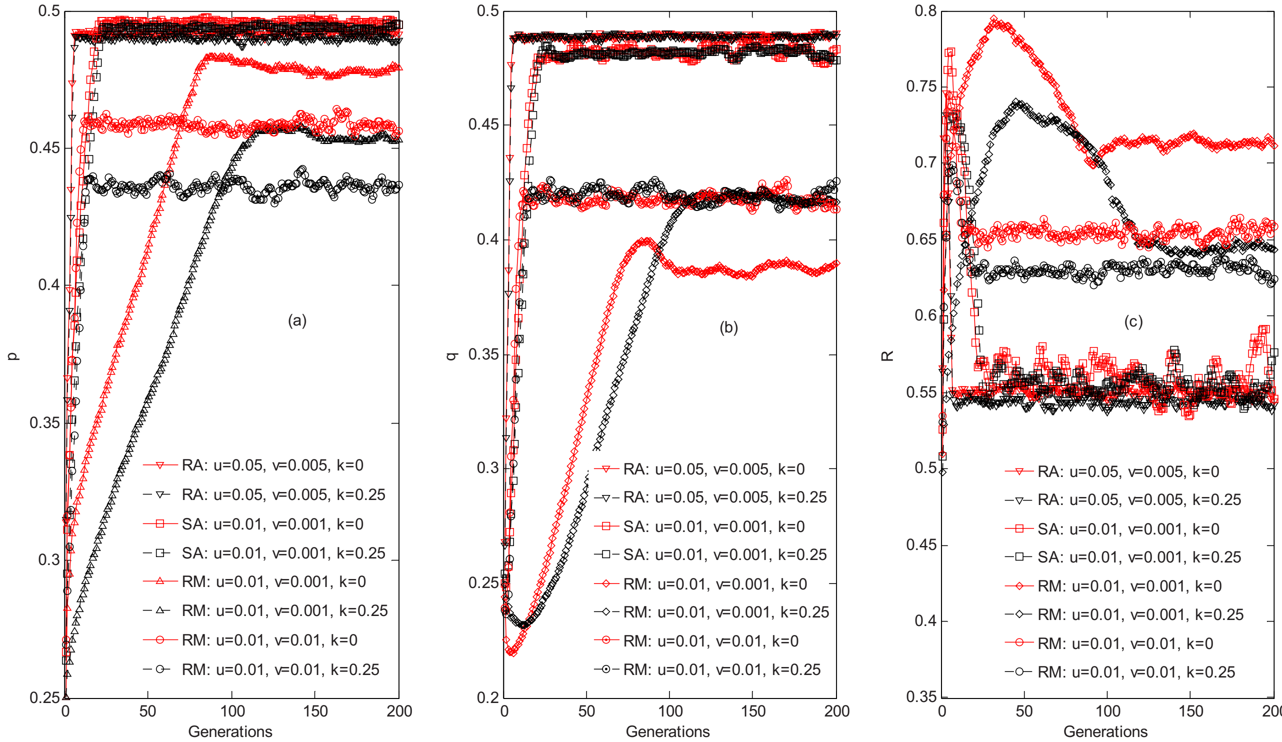

FIG. 1. (Color online) Typical population evolutionary dynamics of the first 200 generations in which each agent has average $r=28$ times to be both proposer and responder in each generation. "R," "S," "A," and "M" are the abbreviations of random network, scale-free network, adding belief update mechanism and multiplying belief update mechanism, respectively. Scale-free networks are generated according the Barabási-Albert model [15]. (a) The evolution process of the average giving rate p. (b) The evolution process of the average asking rate q. (c) The evolution process of the average game payoff per agent per round R.

sponder's asking rate q is not larger than the proposer's giving rate p, the responder and the proposer obtain p and $1-p$ of the monetary sum, respectively. Otherwise, the offer is rejected and both agents obtain nothing. Without doubt, rejection is detrimental to both agents as it results in no earnings. When the ultimatum game is finished, the proposer and the responder update their beliefs simultaneously. If the responder accepts the proposer's offer, the responder increases its asking rate q but the proposer decreases its giving rate p with small values. Conversely, if the responder rejects the proposer's offer, both agents update their beliefs in reverse manners. Let q^b and q^a denote the responder's asking rate before and after playing the ultimatum game respectively; p^b and p^a denote the proposer's giving rate before and after playing the ultimatum game. Two belief update mechanisms are considered in this paper: (1) adding mechanism $q^a=q^b\pm v$ and $p^a=p^b\mp v$ and (2) multiplying mechanism $q^a=q^b(1\pm v)$ and $p^a=p^b(1\mp v)$, where v is often a small constant value.

Let us now describe the evolutionary dynamics of a population consists of N agents with discrete generations. Agents are located on a network which defines the neighborhood of each agent. Considering that the interaction structure plays an important role in the evolutionary dynamics of cooperation and fairness [12–14], we consider two kinds of networks with average degree $2r$ in this work: random network and scale-free network [15]. In each generation, each agent interacts with all of its neighbors and is equally likely to be proposer or responder. Then, each agent will be proposer on average r times and be responder the same number of times. After each agent has participated in all neighborhood pairing ultimatum games, we consider that a game generation has concluded and compute the cumulative game payoff of each agent. Agents are reproduced on the basis of their total payoff obtained by adding a background payoff onto the cumulative game payoff [16]. This is realized by comparing each agent with another randomly chosen agent in the neighborhood and giving an offspring to the one with the higher total payoff. Then, this offspring occupies the site of the one with the lower total payoff. Ultimatum game represents one kind of interactions. The background payoff represents the contributions to fitness that come from other kinds of interaction. It is characterized by the background payoff coefficient k which equals the background payoff divided by r. Like most evolutionary models, each offspring is also subject to potential mutation which may change the offspring's beliefs. Given an agent with beliefs (p,q), its offspring will also hold beliefs (p,q) with probability $1-u$ and adopt beliefs with values drawn at random in (0 0.5] with probability u.

Because agents update their internal beliefs after they accomplished each ultimatum game, it is too difficult to perform mathematical analysis. Therefore, we show the evolutional dynamics only by computer simulations. One run of the model consists of 100 agents and 1000 generations. Each experimental condition is replicated 36 times. In all these simulations the typical behaviors of the system are attained less than three hundred generations and then persist stochastically over the entire 1000 generation period history. That

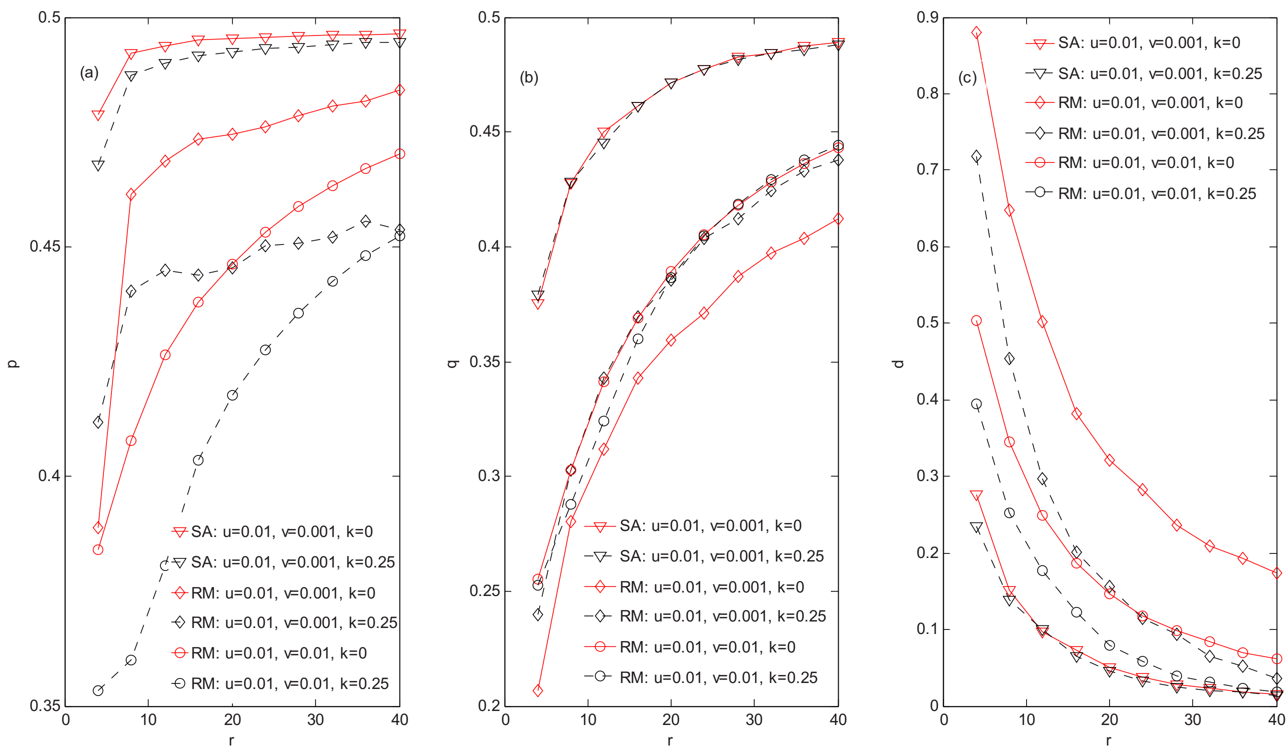

FIG. 2. (Color online) Degree of fairness at steady state influenced by the average number of ultimatum games each agent played in each generation. (a) Measured the average giving rate p as a function of the parameter r. (b) Measured the average asking rate q as a function of the parameter r. (c) Measured the discrepancy rate $d=(p-q)/q$ as a function of the parameter r.

full history is the basis of our reported averages. Our simulation results show that the payoff-oriented mechanism can readily lead to the emergence of fairness behaviors (see Fig. 1). The average giving rate p and the average asking rate q are the averages of the beliefs of all agents; the average game payoff per agent per round R is obtained by using the cumulative ultimatum game payoffs of all agents divided by Nr. If one ultimatum game is successful, it will contribute payoff 1 to the whole population. Otherwise, the ultimatum game contributes nothing to the population. Therefore, R corresponds to the probability of the proposer's off being accepted. The population starts with giving rate and asking rate uniformly distributed over (0 0.5], so the initial average giving rate and asking rate are 0.25, and the initial average payoff per agent per round is 0.5. As we can see from Fig. 1, there are some differences among the evolution speed, the values of p, q, and R in the steady state, which are caused by belief update mechanism, interaction structure, and parameter combination. However, all populations are able rapidly to establish a substantial degree of fairness and evolve to the steady state after 120 generations, regardless of adding or multiplying belief update mechanisms, random or scale-free networks and different parameter values. Unlike other direct or indirect reciprocal evolutionary models required that all players are capable of comparing their own efforts and payoffs with those of others [4,9], our results indicate that fairness behaviors, like cooperative strategies [17], can evolve even under such minimalist assumptions, provided that agents are capable of responding to their own payoff signals of the previous ultimatum game.

Considering that the parameter r characterizes the average number of ultimatum games each agent played with others in one generation, bigger r implies that agents will have more chance to adaptively adjust their internal beliefs. Therefore, we need to examine the role of the parameter r in determining the fairness behaviors at steady state. As shown in Figs. 2(a) and 2(b), both the average giving rate p and the average asking rate q increase with increasing r, and the general trend is close to the universal fairness behaviors 50%-50%. However, the functional relationships between (p,q) and r are influenced by belief update mechanisms, interaction networks, and other parameters. Furthermore, we study the relative changes of p and q with increasing r by defining the discrepancy rate between the average giving rate and the average asking rate as $d=(p-q)/q$. Evidently, higher degree of discrepancy rate implies the proposer's willingness to offer is much higher than the responder's rejection level, which leads to higher acceptance probability in the ultimatum games. As shown in Fig. 2(c), the discrepancy rate d decreases monotonically with increasing r. Therefore, the parameter r exerts opposite effects on the degree of fairness and the acceptance probability of the ultimatum game.

Let us now examine the effects of the background payoff coefficient k in establishing fairness. As agents' fitness is determined by the summation of the background payoff and the ultimatum game payoff, the latter will play a less important role in determining an individual's lifetime fitness when k becomes larger. Unfortunately, the effects of the background payoff are too sensitive to the interaction structure, the belief update mechanism and other parameters. As shown

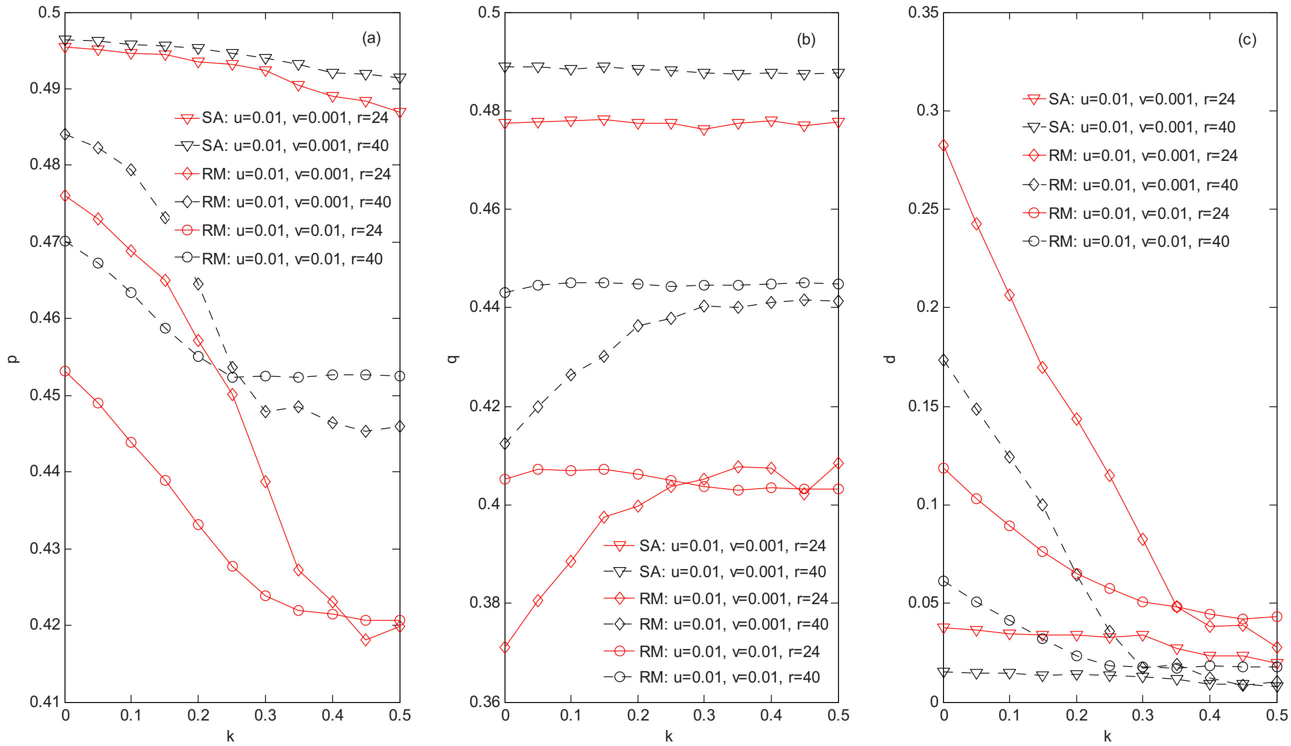

FIG. 3. (Color online) The average giving rate, the average asking rate, and the discrepancy rate shown as a function of the background payoff coefficient at steady state. (a) Measured p as a function of the parameter k. (b) Measured q as a function of the parameter k. (c) Measured d as a function of the parameter k.

in Figs. 3(a)–3(c), p, q, and d change only slightly with increasing k when the scale-free network and the adding belief update mechanism are used in computer simulations (see curves labeled as "SA"). However, p decreases and q increases sharply with increasing k while the random network and the multiplying belief update mechanism are used in computer simulations (see curves labeled as "RM $v=0.001$"). It is difficult to conclude some consistent results about how p and q are influenced by k. However, as shown in Fig. 3(c), there is a general trend that the discrepancy rate d decreases with increasing k. This result suggests that the background payoff might not exert direct influences on the degree of fairness, but lead to suppress agents' relative willingness to offer more to and require less from their opponents. McNamara *et al.* first introduced the background fitness contribution in evolutionary model and illustrated its importance in the evolution of cooperation [16]. However, our results show its importance might not be much significant in the evolution of fairness.

In our model, each agent has average r times to be proposer and responder in his lifetime. The average cumulative game payoff divided by r is called as the average game payoff per agent per round R. Evidently, R also equals the probability of the proposer's offer being accepted in one ultimatum game. Though larger r leads to higher p and q in steady state, R decreases significantly with increasing r [see in Fig. 4(a)]. Therefore, we can infer that higher degree of fairness does not certainly improve the average game payoff per agent per round. Mathematically, the acceptance probability in ultimatum game can be computed based on the discrepancy rate d if the probability distribution functions of random variables p and q is known. Combining Figs. 2(c) and 4(c), we can conclude that larger r will degrade R by lowering d. In other words, the number of ultimatum games played by each agent in one generation influences the acceptance probability first, and then changes agents' relative game payoffs. The similar logic can also be applied to analyze the effect of the background payoff coefficient. In the simulations with SA, both d and R vary little with increasing k [see Figs. 3(c) and 4(b)] and the corresponding curves in Fig. 4(c) are very short. Conversely, in the simulations with "RM $v=0.001$," d and R decrease significantly with increasing k and the corresponding curves are much longer.

Following we examine a special case by setting mutation probability $u=0$, which means that there is no mutation in the evolutionary dynamics. As we can see from Fig. 5, the ultimatum game will reach at 50%-50% fair split, regardless of different belief update mechanisms, interaction structures, and parameter combinations used in simulations. In steady state, the average giving rate, the average asking rate, and the average game payoff per agent per round are all 0.5. We also note that there are some differences in the evolution process before the evolutionary dynamics reaches at the evolutionary stability state. For example, the population will evolve to the steady state more quickly with larger r. Considering that our concerns are mainly focused on the steady state, we are not planning to discuss those minor differences in this paper. We should point out that R would be 1 rather than 0.5 if the population evolves to an ideal state in which each agent holds fairness beliefs $(p,q)=(0.5,0.5)$. However, the population will evolve toward, but never reach at the ideal state in limited time because of the belief update mechanisms used in our model.

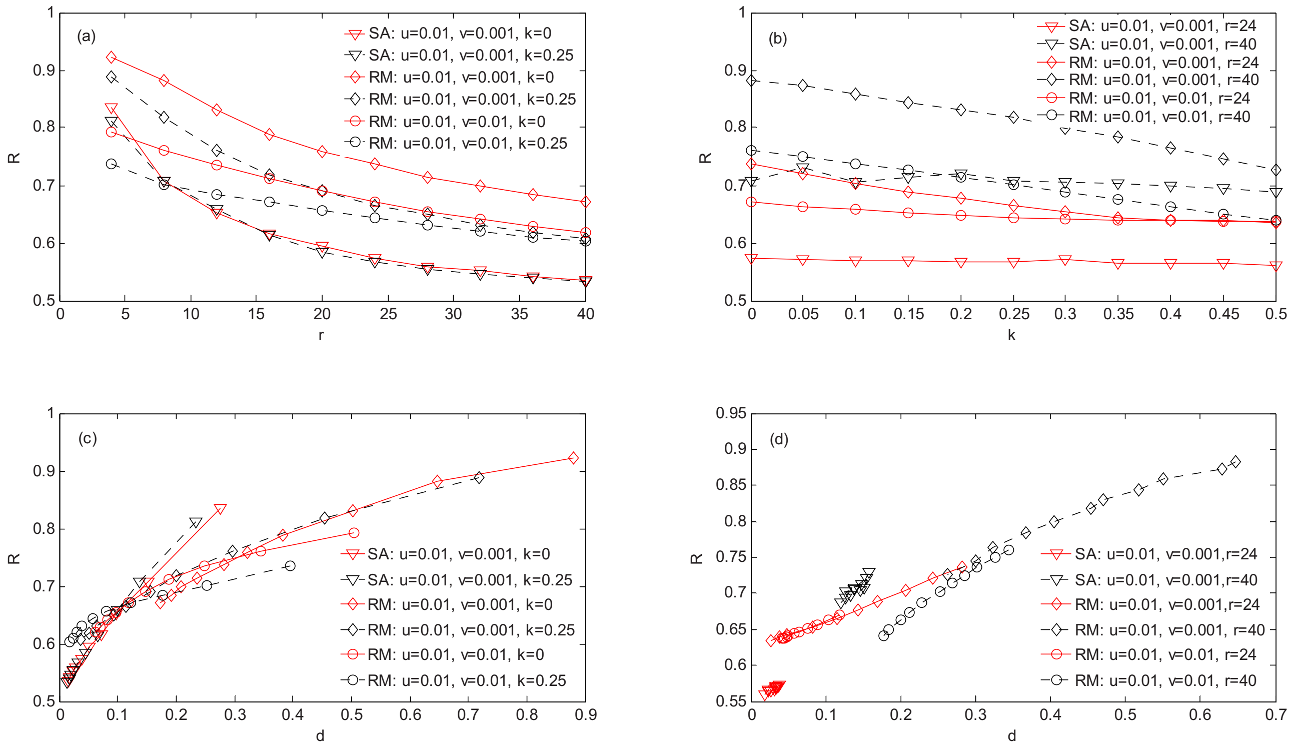

FIG. 4. (Color online) The average game payoff per agent per round influenced by the number of ultimatum games and the background payoff coefficient. (a) Measured R as a function of the parameter r. (b) Measured R as a function of the parameter k. (c) Measured R as a function of the discrepancy rate d when r changed from 4 to 40. (d) Measured R as a function of the discrepancy rate d when k changed from 0 to 0.5.

As we can see from Figs. 1–5, the interaction structure plays a role in determining the evolution process, the degree of fairness and the average game payoff per agent per round in steady state. Roughly speaking, compared with random networks, the evolutionary dynamics evolves to the steady state more quickly, and leads to higher degree of fairness and lower average game payoff per agent per round when agents are located on scale-free networks.

As incorporated adaptive dynamics in one generation and evolutionary dynamics among generations, our model extends the insight of Nowak *et al.* [9] by reducing the requirements for the participating agents: both the proposer and the responder take action only based on their own internal beliefs. Unlike the empathy model required that a fixed proportion of agents employing strategies with $p=q$ [18], the initial values of agents' giving rate and asking rate are chosen at random, and then update independently in the evolution process. Furthermore, our results show that fairness behaviors can emerge out regardless of the interaction structure, which is different from structure dependent fairness models [13,14]. In our model, the emergent fairness behaviors do not require any agent being capable of remembering its previous interactions with other agents, observing and recalling how the other agents behaved with third parties [19]. Agents are only required very limited adaptive capability of updating their fairness beliefs based on their previous payoff signals. Therefore, the payoff-oriented model could be widely applicable in situations where agents are nonhumans with extremely low

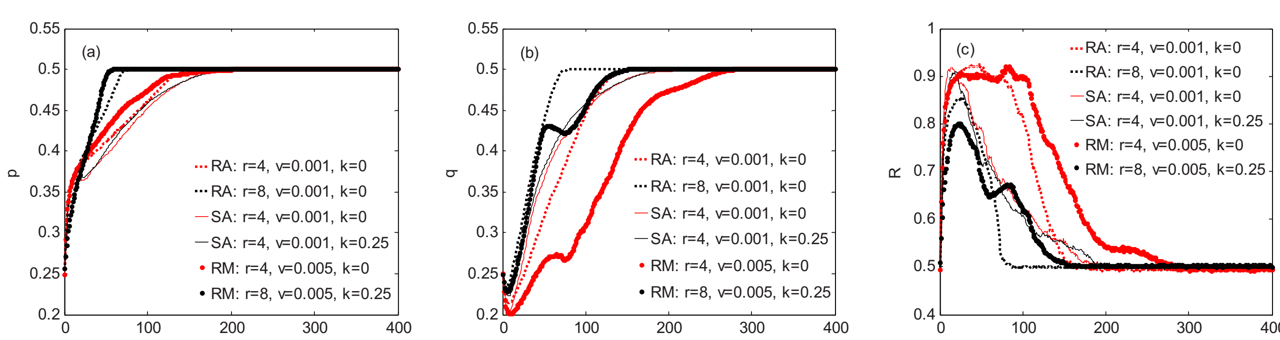

FIG. 5. (Color online) Typical population evolutionary dynamics of the first 400 generations with mutation probability $u=0$. (a) The evolution process of the average giving rate p. (b) The evolution process of the average asking rate q. (c) The evolution process of the average game payoff per agent per round R.

intelligence. For example, there is ongoing debate about whether chimpanzees are tolerant of unfairness. It was reported that chimpanzees are sensitive to unfairness and are negatively reciprocal [4]. However, other researchers' experiments have shown that chimpanzees are rational maximizers when food was involved [20]. These conflicting experimental phenomena can be reconciled in our model that chimpanzees (agents) might not compare their own rewards and efforts with those of others, but their fairness behaviors make people to draw the conclusion that they are sensitive to unfairness.

In summary, our results have shown that fairness behaviors can be established and sustained in a population consists of zero intelligence agents without any strategic reasoning and memory. The evolutionary dynamics will lead to 50%-50% fair split provided that there is no mutation. Higher degree of fairness can be attained if agents have more chance to play the ultimatum game with others in each generation, but it does not certainly lead to higher acceptance probability in the ultimatum game and higher average game payoff per agent per round, which depend on the discrepancy rate between the average giving rate and the average asking rate rather than on the absolute degree of fairness.

This work was supported by the National Natural Science Foundation of China under Grant No. 70701030 and Zhejiang Provincial Natural Science Foundation of China under Grant No. Y607001.

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