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Evolution of cooperation driven by social-welfare-based migration

Yan Li, Hang Ye, Hong Zhang *

College of Economics and Interdisciplinary Center for Social Sciences (ICSS), Zhejiang University, Hangzhou 310027, PR China

HIGHLIGHTS

- Individuals use social welfare evaluation to determine their migration behavior.
- The effects of different social welfare functions on cooperation are investigated.
- Social welfare functions have different relative efficiency for supporting cooperation under different parameter ranges.
- Inequality aversion plays an important role in the evolution of cooperation.

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ABSTRACT

Individuals' migration behavior may play a significant role in the evolution of cooperation. In reality, individuals' migration behavior may depend on their perceptions of social welfare. To study the relationship between social-welfare-based migration and the evolution of cooperation, we consider an evolutionary prisoner's dilemma game (PDG) in which an individual's migration depends on social welfare but not on the individual's own payoff. By introducing three important social welfare functions (SWFs) that are commonly studied in social science, we find that social-welfare-based migration can promote cooperation under a wide range of parameter values. In addition, these three SWFs have different effects on cooperation, especially through the different spatial patterns formed by migration. Because the relative efficiency of the three SWFs will change if the parameter values are changed, we cannot determine which SWF is optimal for supporting cooperation. We also show that memory capacity, which is needed to evaluate individual welfare, may affect cooperation levels in opposite directions under different SWFs. Our work should be helpful for understanding the evolution of human cooperation and bridging the chasm between studies of social preferences and studies of social cooperation.

1. Introduction

Cooperation is a ubiquitous phenomenon in both human society and animal world. It is a fascinating challenge in both natural science and social science to understand how cooperation can emerge and be maintained in communities of selfish individuals [1–6]. The evolutionary prisoner's dilemma game (PDG) has been a widely used metaphor for understanding cooperation between unrelated individuals. In a one-shot PDG, two players simultaneously choose between two strategies: cooperation and defection. Although mutual cooperation leads to the optimal outcome, defection is always a better choice for any self-interested individual regardless of the partner's choice. To understand how cooperation can be favored in nature and

* Corresponding author.
E-mail address: poyeker@gmail.com (H. Zhang).

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human society, five major mechanisms for supporting cooperation have been proposed, including kin selection [7], direct reciprocity [8], indirect reciprocity [9], spatial selection [10] and multilevel selection [11]. A central problem in investigations of these mechanisms is how assortment among individuals can emerge in the process of evolution. If such assortment is at work, cooperators can interact more frequently with other cooperators but not with defectors. As a remarkable example, in the spatial PDG, cooperation can emerge and be maintained if cooperators can form clusters such that they have greater payoffs than defectors due to the effect of spatial reciprocity.

In recent years, as an important factor in the spatial PDG, the migration of players under various conditions has been introduced and investigated. For example, Vainstein et al. [12] introduced empty sites and random migration in a spatial PDG and found that such movement can enhance cooperation under a wide variety of conditions. Vainstein and Arenzon [13] extended such random migration to Snowdrift games. In addition to random migration, some forms of adaptive or contingent migration also have been investigated. Aktipis proposed a walk-away strategy whereby individuals can avoid repeated interactions with defectors [14]. Helbing et al. proposed a model of success-driven migration in which individuals prefer moving to sites with high expected payoffs [15]. Liu et al. [16] added the factor of migration cost to the success-driven model and found that migration cost does not suppress the emergence of cooperative behavior. Yang et al. [17] considered a migration mechanism based on wealth, and Cong et al. [18] discussed reputation-based migration on the lattice. In addition to migration on a square lattice, studies have also discussed the effect of migration in continuous two-dimensional space where agents interacted and moved on a plane [19–22]. Various other forms of migration can enhance cooperation under certain parameter ranges [23–28]. These investigations are meaningful not only because migration provides a new approach to understanding the evolution of cooperation but also because migration itself is a key property of humans and a fundamental problem in understanding population dynamics [29,30].

In most previous studies of contingent migration, the migration behavior of each individual is entirely based on the individual's own situation and not on the situations of other individuals. This means that individuals care about information concerning other individuals only when this information can influence their own situation. However, in real society, people often have social preferences [31,32,2,33], by which an individual may consider another individual's payoff in addition to its own. Chen et al. [34] and Wang et al. [35] considered the neighbor's payoff and information during strategy updating and found that these mechanisms can enhance cooperation under certain parameters. Bo [36] discussed the effect of inequality aversion, which is a commonly used form of social preferences in the PDG on complex networks. Lu et al. [37] also considered the effect of a version of social preferences on the evolution of cooperation in a self-questioning game. Cushing [38] discussed the relationship between migration and social welfare under certain conditions using data from US and found that social welfare has an effect on migration decisions. In this paper, we introduce social welfare evaluation as a type of social preferences into individuals' contingent migration decisions and investigate how different social welfare evaluation modes affect migration patterns and cooperation. By social welfare, we mean individuals' evaluation of the situation of a given site in the lattice. In previous works about adaptive migration [15,26], a focal player need to know the strategies of the players in the empty site's neighborhood to decide whether to migrate. Unlike this information setting, in our model the information needed for deciding the migration behavior is only the aggregated social welfare of the site under consideration. Although the social welfare of a given site is derived from the past history of the payoffs of the players in the neighborhood, the focal player does not need to know any information about the strategies or payoffs of other players. We assume that individuals are ignorant of their own welfare when they decide to improve their environment, which means that this evaluation depends solely on the welfare of neighboring individuals and not on that of the focal individual who chose to migrate. Because social welfare depends on all the welfare of individuals under consideration, we face the problem of how to measure social welfare using some aggregation method [39–41]. To address this problem in our model, three types of cardinal social welfare functions (SWFs) are considered: the Utilitarian SWF, Bernoulli–Nash SWF, and Rawlsian SWF. According to these SWFs, each individual's migration behavior will be contingent on the welfare of other individuals and may affect the individual's strategy updating. Interestingly, we find that the three SWFs have different effects on both the migration patterns and the evolution of cooperation. This paper proceeds as follows: we first describe the model and then present our findings in detail.

2. Model

In a one-shot PDG, each player independently chooses either cooperation or defection. R ("reward") represents the payoff for mutual cooperation, while P ("punishment") represents the payoff for mutual defection. T ("temptation") represents the payoff for unilateral defection, which leads to the payoff S ("sucker") for the cooperative individual. If the inequalities $T > R > P > S$ and $2R > T+S$ both hold, the payoff structure satisfies the conditions of the classical PDG. For simplicity, although there are some alternative scaling methods for the PDG [42], we adopt the re-scaled payoff matrix: $T = b > 1$, $R = 1$, and $P = S = 0$ to allow us to study the game as a function of a single "temptation" parameter b. We consider an evolutionary PDG on an $L \times L = N$ square lattice (L is fixed at 50 in our simulations) with periodic boundary conditions [10,43]. Each site on the lattice is either empty or occupied by an individual. We define the density of players $\rho = n/N$ as a parameter, where n is the number of all individuals. Initially, individuals are randomly located on the lattice, and their strategies (cooperation or defection) are assigned with equivalent probability.

Individuals are updated asynchronously in a random sequential order at each time step. The randomly selected individual engages in interactions with its 4 nearest neighbors (the von Neumann neighborhood) and compares its payoff with that of its neighbors. If the richest neighbor's payoff is larger than that of the focal individual, the focal individual will copy the strategy of this neighbor with probability $1-\mu$. With probability μ, the individual randomly resets its strategy. The resulting strategy mutation can be seen as environmental noise or trial-and-error behavior by individuals. Before updating strategy, the individual has a chance to decide whether to leave its current position by comparing the evaluated social welfare of two sites. If possible, an empty site in the neighborhood will be chosen, and the social welfare of this site and the currently occupied site will be evaluated and compared using an SWF.

We assume that the payoffs of individuals are memorized and accumulated to determine their individual welfare. Specifically, the welfare of each individual i is the summation of its payoffs over the past h time steps. For each time step t:

$$w_j = \sum_{t-h-1<k\leq t-1} p_{j,k}$$

where w_j is the individual welfare of j and $p_{j,k}$ is the payoff of j at time step k (it is calculated when the individual is selected to update).

As mentioned above, three different SWFs are considered in this study to determine the social welfare of compared sites. Utilitarian (or Benthamian) SWF measures the sum of all individual welfare [44]:

$$W_{U,i} = \sum_{j\in M_i} w_j$$

where W is the social welfare, w_j is the welfare of individual j, and M_i is the set of all individuals in the neighborhood of site i.

Bernoulli–Nash SWF measures the product of all individual welfare [45]:

$$W_{B\text{–}N,i} = \prod_{j\in M_i} w_j.$$

Finally, Rawlsian SWF measures the minimum of all individual welfare [46]:

$$W_{R,i} = \min(w_j), \quad j \in M_i.$$

We can see that both $W_{B\text{–}N}$ and W_R have implications for equality, which means that these two SWFs are more sensitive to a change in the welfare of a poorer individual than to the same change of a richer individual. Specifically, W_R can be regarded as an extreme case of an inequality-averse SWF because it only considers the poorest individual's welfare. In $W_{B\text{–}N}$, individuals have heterogeneous influences on social welfare, and hence it is commonly considered a combination of W_U and W_R. As an important social preference of humans, inequality aversion is a widely studied topic in social science [47,48]. By introducing SWFs and social welfare comparisons in the analysis of migration behavior, we can investigate the role of social welfare and inequality aversion in the evolution of cooperation.

After comparing two sites' social welfare, if the new site's social welfare is higher than that of the original site, the individual will move to the new site; otherwise, the individual will remain at the original site. Following common practice, if an individual is isolated, it will be forced to move to a randomly chosen neighboring site. In addition, we assume that individuals have a chance (with probability γ) to randomly move to a new site without considering the relative social welfare of the sites. Both strategy mutation and random migration can be interpreted as noise in the evolutionary system or uncertainty in decision making.

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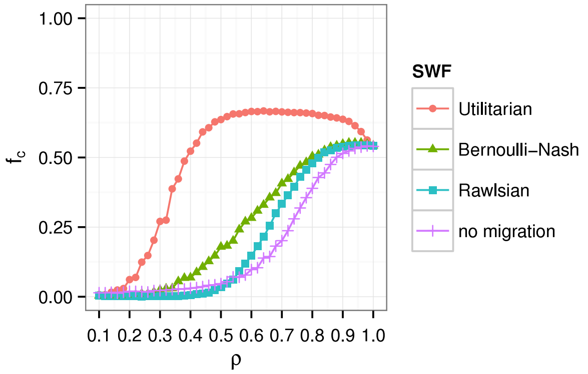
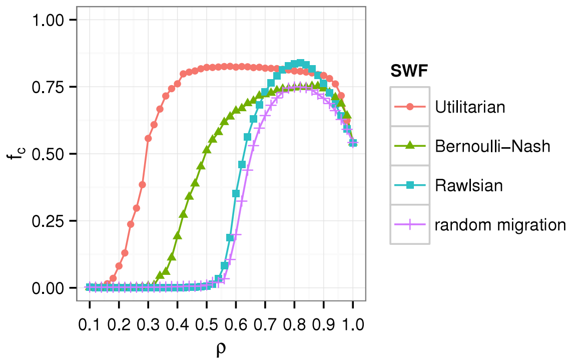
The simulation procedure of our model is summarized as follows:
Initialize
For each time step:
    For each agent:
        Migrates according to different SWFs (or randomly migrates).
        Interacts with its Von Neumann neighbors and calculates its payoff.
        Learns strategy according to the richest following rule.
        Mutates.
    End
End
```

3. Results

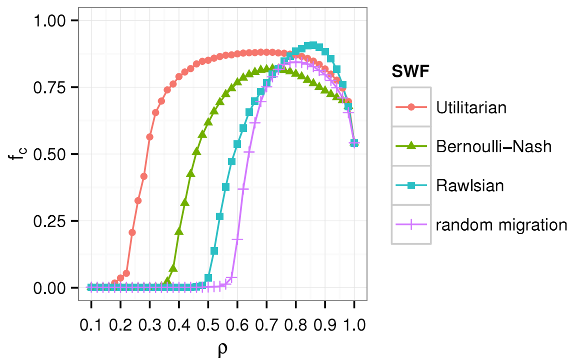
In what follows, as the most important quantity for characterizing the system, f_c is defined as the fraction of cooperators in the whole population. Computer simulations of our model show that social-welfare-based migration significantly affects the emergence of cooperation in the system. Fig. 1 shows the dependence of the cooperation level on the population density (ρ) for different SWFs under different noise conditions. The results of the degenerated model without migration ($\gamma = 0$) or with pure random migration ($\gamma = 0.01$ or $\gamma = 0.05$) are also shown in Fig. 1 to allow us to compare our model with those of previous studies. As can be seen in Fig. 1, the cooperation levels under the three SWFs are higher than under the no migration case or random migration case for most population densities. In Fig. 1(b) and (c), we see that random migration can change the effects of SWF-based migration. For all of the SWFs, the cooperation levels are enhanced when random



(a) $\gamma = 0$.



(b) $\gamma = 0.01$.



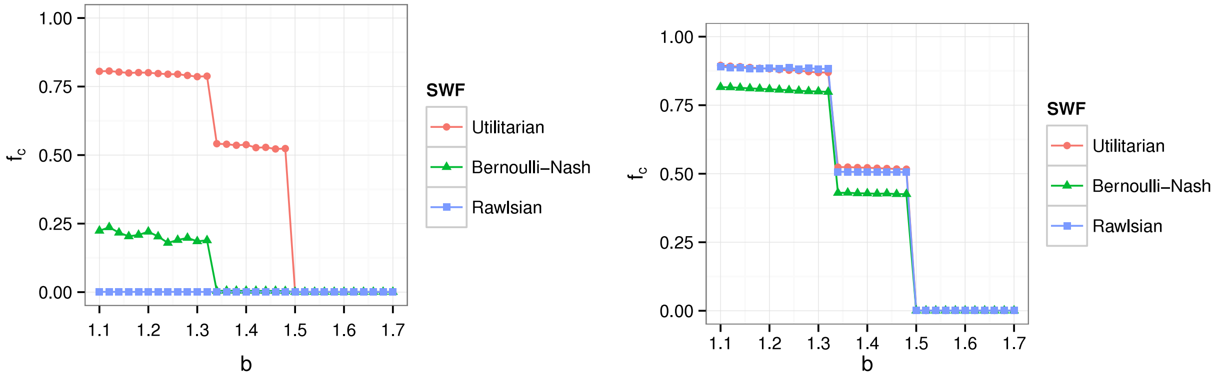
(c) $\gamma = 0.05$.

Fig. 1. The density of cooperators f_c as a function of population density ρ for different SWFs under different migration noise levels. Other parameters: $b = 1.3$, $\mu = 0.001$, $h = 5$. The fraction of cooperators is obtained by averaging over 5000 time steps after 10 000 time steps and each data point is averaged over 40 different realizations.

migration is introduced. When $\gamma = 0$, f_c cannot exceed a moderate level (near 55%) under both $W_{B\text{–}N}$ and W_R. Only when γ is higher (Fig. 1(b) and (c)), can high levels of cooperation be achieved under $W_{B\text{–}N}$ and W_R. However, under W_U, there is always an optimal region of ρ for high levels of cooperation ($f_c > 60\%$) whenever random migration is in effect. This result highlights the relatively high efficiency of W_U. For example, even when $\gamma = 0$, high levels of cooperation ($f_c > 60\%$) can be achieved by using W_U, while there is no region of ρ for high cooperation levels under $W_{B\text{–}N}$ and W_R. Moreover, we can see that although high levels of cooperation can be achieved under all of the three SWFs when random migration is introduced, the region for high cooperation levels is larger under W_U than under $W_{B\text{–}N}$ and W_R. However, the highest level of cooperation that the system can achieve is generated by W_R but not W_U (see Fig. 1(b) and (c)), though W_U outperforms W_R for most population densities. This result indicates that we cannot determine which SWF is better for supporting cooperation if we have no knowledge of the system environment. Fig. 1 also shows crucial differences among the results generated by the different SWFs. First, although all of the SWFs have best regions for supporting cooperation, the positions of these regions are different. While W_U has a large best region, the best regions for $W_{B\text{–}N}$ and W_U are at very high ρ. Furthermore, to compare the three SWFs, we can roughly separate Fig. 1(c) into some parts, including the low population density part ($\rho < 0.75$) and high population density part ($\rho > 0.79$). As we can see, the relative efficiency in supporting cooperation under different SWFs will be reversed if ρ changes from a low to a high level. If ρ is small (<0.75), W_U outperforms $W_{B\text{–}N}$ and W_R, while W_R outperforms $W_{B\text{–}N}$ and W_U if ρ is high (>0.79). We also see that although $W_{B\text{–}N}$ can be seen as a mix of W_U and W_R by definition, the cooperation levels enhanced by $W_{B\text{–}N}$ are not always a mix of those enhanced by W_U and W_R.

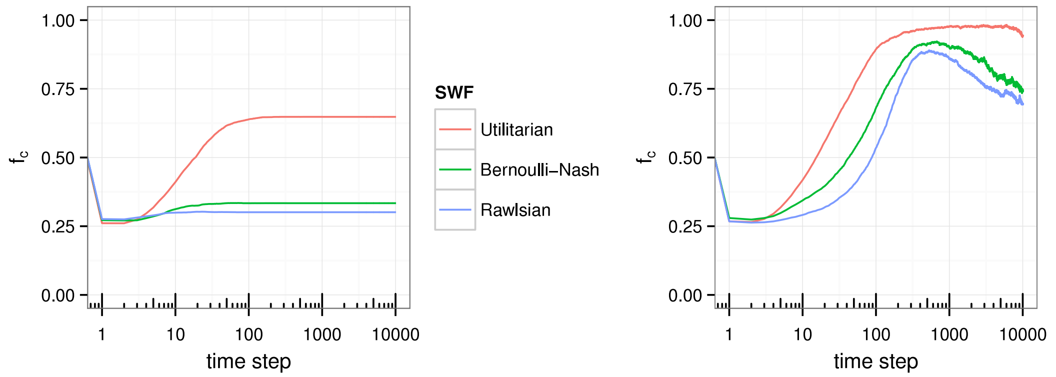
The dependence of f_c on b is shown in Fig. 2. We see that f_c exhibits discontinuous transitions, which are also found in other migration-based models. However, if population density is low ($\rho = 0.4$), W_R never leads to high f_c (cooperators become extinct for all values of b). In fact, if ρ is small, W_U outperforms $W_{B\text{–}N}$ and W_R for all values of b. As population density increases ($\rho = 0.8$), the result is changed significantly. While the cooperation levels generated by W_U are only increased slightly, the increase in ρ significantly changes the relative efficiency of the three SWFs. The increases in f_c for both $W_{B\text{–}N}$ and W_R are more significant than for W_U. Although W_U still outperforms $W_{B\text{–}N}$ and W_R, the differences of cooperation levels among the three SWFs are reduced significantly by the increase in ρ. In other words, the efficiency of $W_{B\text{–}N}$ and W_R for promoting cooperation will be similar to that of W_U under high population densities.

To better understand the effects of SWF-based migration on cooperation, we will examine the evolutionary dynamics and spatial patterns in some typical simulation runs and investigate how SWF-based migration shapes the evolutionary

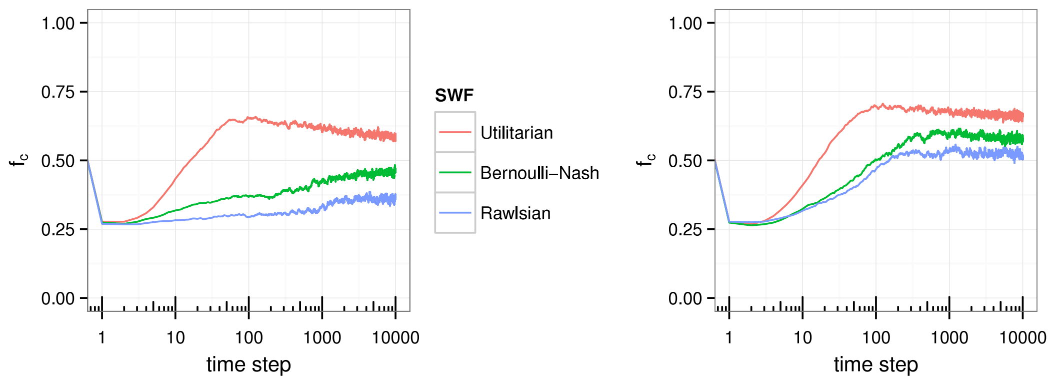


(a) $\rho = 0.4$. (b) $\rho = 0.8$.

Fig. 2. The fraction of cooperators as a function of b for different SWFs under different population densities. Other parameters: $\mu = 0.001$, $\gamma = 0.05$, $h = 5$. The fraction of cooperators is obtained by averaging over 5000 time steps after 10 000 time steps and each data point is averaged over 20 different realizations.



(a) $\mu = 0, \gamma = 0$. (b) $\mu = 0, \gamma = 0.01$.



(c) $\mu = 0.01, \gamma = 0$. (d) $\mu = 0.01, \gamma = 0.01$.

Fig. 3. The fraction of cooperators as a function of time step t for different SWFs under different noise conditions. Other parameter: $\rho = 0.7$, $b = 1.3$, $h = 5$.

characteristics of the system. First, the evolution of f_c over time is plotted in Fig. 3. In most cases, W_U quickly leads to high cooperation levels after approximately 100 time steps, and high cooperation levels can be maintained over time. For $W_{B\text{–}N}$ and W_R, the evolutionary paths are more sensitive to the noise conditions in the system. We see that although the relative efficiency of the SWFs will not be changed when μ and γ are changed, the changes in noise conditions can affect the evolutionary paths for all of the three SWFs. For example, when there is no strategy noise, random migration ($\gamma = 0.01$) can significantly enhance the cooperation levels especially for $W_{B\text{–}N}$ and W_R. In fact, only when random migration is in effect, high levels of cooperation can be achieved by using $W_{B\text{–}N}$ or W_R. However, f_c will gradually decline to moderate levels after the emergence of cooperation, which is different from the evolutionary path under W_U (see Fig. 3(b)). In Fig. 3(c) and (d), it

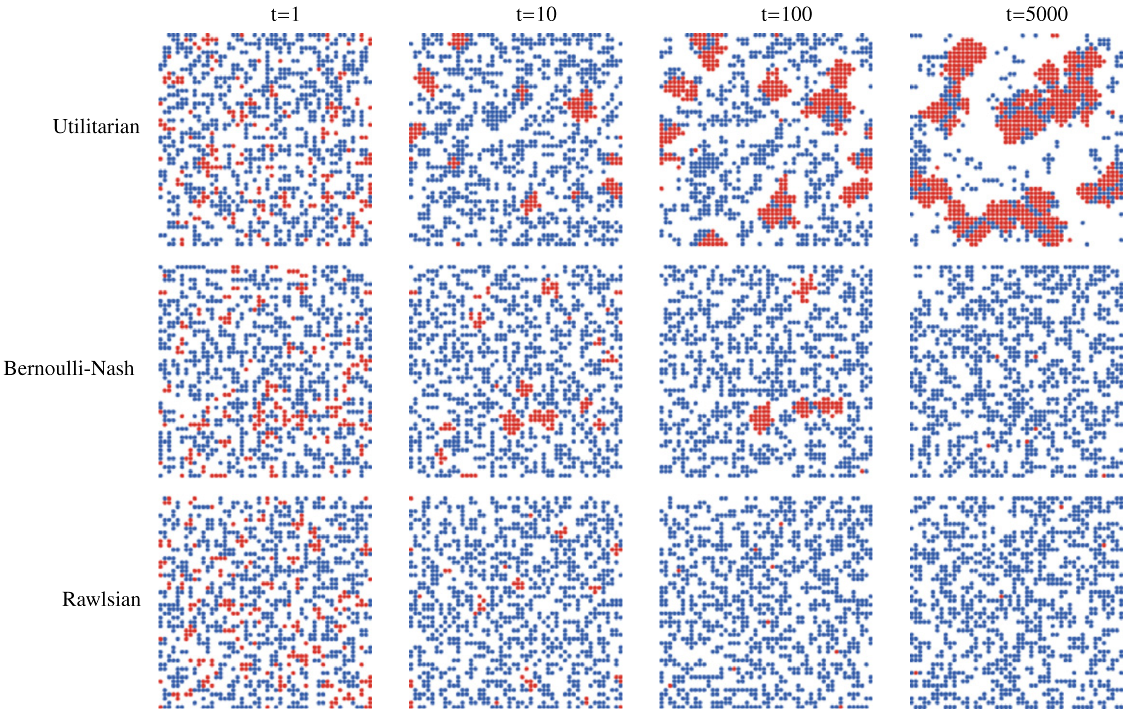


Fig. 4. Typical snapshots of distributions of cooperators (in red) and defectors (in blue) at different time steps for different SWFs under low population density ($\rho = 0.4$). Other parameters: $b = 1.3$, $\mu = 0.01$, $\gamma = 0.01$, $h = 5$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

is shown that strategy noise will not only reduce f_c for most cases (except for W_{B-N} and W_R when $\gamma = 0$) but also reduce the difference of evolutionary paths among the three SWFs. Moreover, we see that although cooperation can be enhanced by random migration, the results are less sensitive to migration noise if strategy noise is in effect.

Let us now focus on the spatial patterns generated by the migration mechanism from the typical snapshots shown in Figs. 4 and 5. As a crucial characteristic of spatial games, cluster formation plays a significant role in the emergence of cooperation. We can see that cooperation cannot emerge if no cluster can be formed, which is consistent with previous studies. When population density is low, only W_U can help the population to form clusters to allow cooperation to emerge and be maintained. However, when strategy noise is in effect, cluster formation is not a sufficient condition for high cooperation levels. For example, although some cooperative clusters can be formed in the population under W_{B-N}, these clusters soon disappear through strategy mutations. When population density is high, we can observe some different cluster patterns, which can explain why the cooperation levels are different under these SWFs. W_U leads to large clusters which can soon absorb almost all the individuals in the population. In the meanwhile, there are some large vacant spaces between clusters where almost no individuals exist. However, when W_{B-N} or W_R is at work, there are some isolated defectors or small defective clusters in the population, indicating that the migration based on W_{B-N} or W_R cannot lead to an optimal cluster structure which can effectively prevent mutant defectors from invading the formed cooperative clusters.

Next, we seek to explain the evolutionary dynamics and spatial patterns for different SWFs in greater detail. For all of the three SWF, we found that there is a demonstrable enduring (END) period and an expanding (EXP) period [49–52] in the evolution over time, and the evolutionary path is sensitive to the introduction of strategy noise and random migration. The cooperation level first rapidly decreases during the END period and then shows an increase during the EXP period. After END period, many defectors and some small cooperative clusters are distributed in the population. The social welfare of the cooperative neighborhood is higher than the defective one, and hence the cooperators have an opportunity to move toward the cooperative neighborhood. Moreover, an agent situated on the boundary of a cooperative cluster will copy the cooperation strategy during strategy updating. Therefore, the cooperative clusters can survive and expand until the system reaches a steady state during the EXP period. The SWF-based migration increases the likelihood that cooperators can escape from the neighboring defectors. However, the introduction of strategy noise (see Fig. 3(c) and (d)) causes many cooperators to become defectors, thereby inhibiting the formation of cooperative clusters. The mutation also causes many defectors to become cooperators, and hence the cooperation levels exhibit significant fluctuation. When there is no strategy noise, although the time required for cooperation to reach a steady state cannot be shortened, the achievable levels of cooperation will be increased by the introduction of random migration. The cooperators have an opportunity to move toward the cooperative neighborhood due to the migration, and the same is true for the defectors. However, the random migration can reduce the opportunity for the defectors to move toward the cooperative neighborhood, and thus the cooperation level

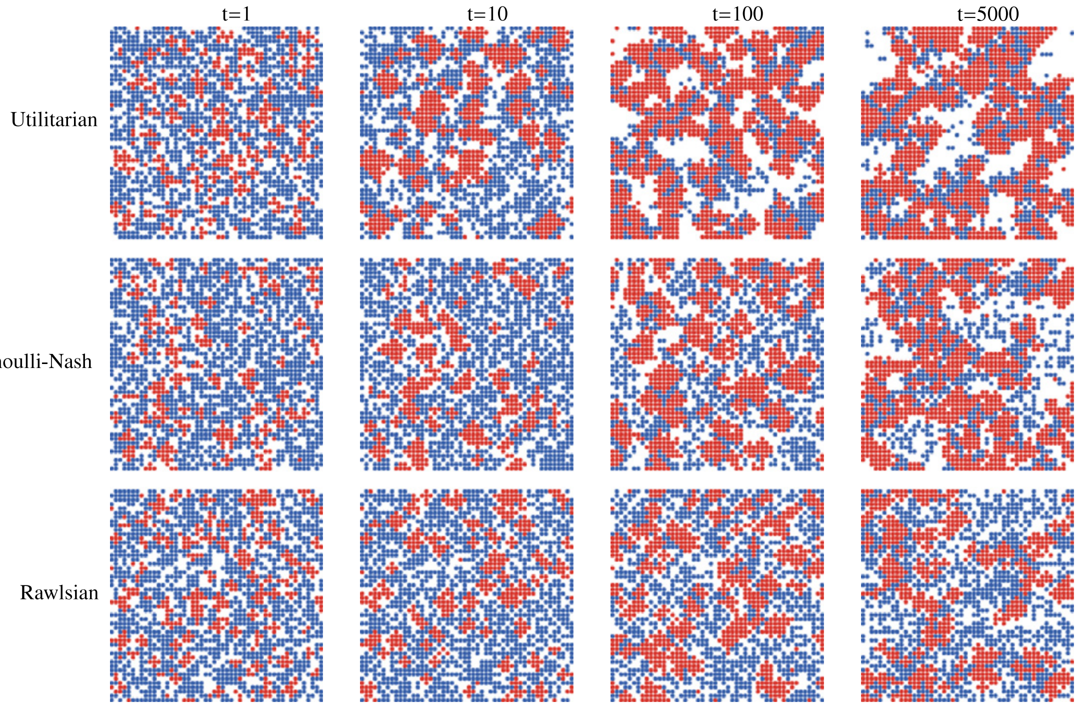


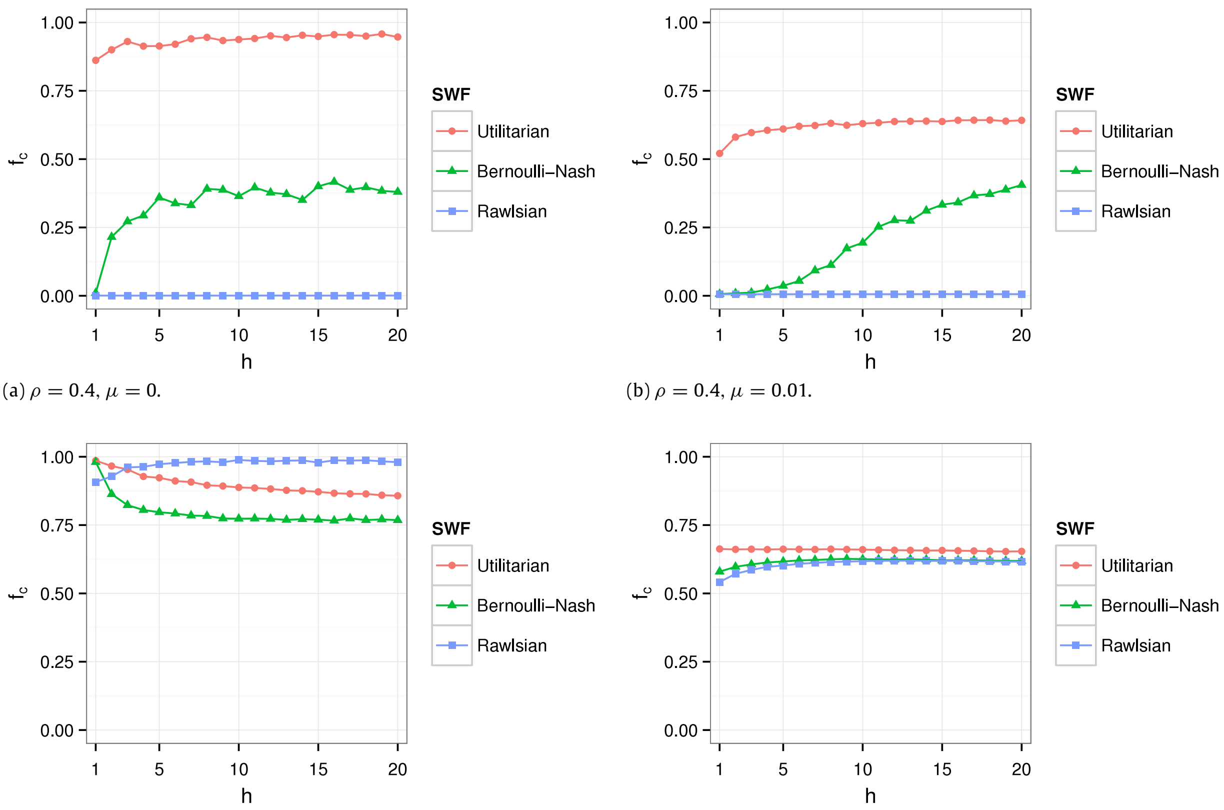
Fig. 5. Typical snapshots of distributions of cooperators (in red) and defectors (in blue) at different time steps for different SWFs under high population density ($\rho = 0.7$). Other parameters: $b = 1.3$, $\mu = 0.01$, $\gamma = 0.01$, $h = 5$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

can be increased quickly. Compared with the Bernoulli–Nash SWF and Rawisian SWF, the Utilitarian SWF is more efficient in forming the cluster structure which is optimal for supporting cooperation. For the Bernoulli–Nash SWF, we can see that when the welfare of a neighboring agent is 0, the social welfare of the neighborhood is 0; thus, the welfare of a poor agent will be emphasized in the calculation of social welfare. In this regard, the Bernoulli–Nash SWF is similar to the Rawisian SWF. However, when the welfare of the agents is non-zero, the Bernoulli–Nash SWF magnifies the difference, which is similar to the Utilitarian SWF. Therefore, the result can be understood as a combination of the results for the Utilitarian SWF and Rawisian SWF (in Fig. 3).

We note that individuals use past history to determine their welfare. Thus, the system requires memory capacity, which may have its own influence on the evolution of cooperation. To address this question, we also examine whether memory capacity affects cooperation levels under typical conditions (Fig. 6). Surprisingly, high memory capacity has a detrimental effect on cooperation under W_U and $W_{B\text{–}N}$ when population density is high and there is no strategy noise. In this case, if h is very small, the system can reach very high cooperation levels under both W_U-based and $W_{B\text{–}N}$-based migration. This result is similar to some previous studies that suggested that memory can notably support cooperation but that excessive memory capacity may also inhibit cooperation under certain circumstances [53–55]. The effect of memory capacity on cooperation for W_R is dependent on whether there is strategy noise. When strategy noise is in effect, higher memory capacity leads to higher cooperation levels for $W_{B\text{–}N}$. However, the levels of cooperation almost cannot be affected by the change of h for W_U (see Fig. 6(d)). If population density is low (Fig. 6(a) and Fig. 6(b)), while cooperation always fails to emerge under W_R, higher memory capacity leads to higher cooperation levels for both W_U and $W_{B\text{–}N}$. Especially for $W_{B\text{–}N}$, as h is increased to high levels, the system can reach moderate cooperation levels, while cooperation cannot emerge without high memory capacity. Interestingly, Fig. 6(c) and (d) shows that the relative efficiency in supporting cooperation of the three SWFs will be changed if the memory capacity is changed. For low memory capacity ($h \leq 2$), W_U outperforms W_R and $W_{B\text{–}N}$. As the memory capacity is increased to higher levels, W_R will benefit from this increase and can serve as a means of supporting very high levels of cooperation. This result shows again that we cannot determine which SWF is better for supporting cooperation if the parameter values are unknown.

4. Conclusion

Experimental economics and behavioral science have shown that individuals have social preferences [56–58]. However, a need persists for studies on the effects of these preferences on the evolution of cooperation, especially in the context of the PDG. As an important type of social preference, social welfare evaluation plays a significant role in determining patterns of individual behavior. Therefore it is worth investigating whether introducing social welfare evaluation affects cooperation in



(a) $\rho = 0.4$, $\mu = 0$.

(b) $\rho = 0.4$, $\mu = 0.01$.

(c) $\rho = 0.8$, $\mu = 0$.

(d) $\rho = 0.8$, $\mu = 0.01$.

Fig. 6. The fraction of cooperators as a function of h for different SWFs under different strategy mutation rates. Other parameters: $b = 1.3$, $\gamma = 0.01$. The fraction of cooperators is obtained by averaging over 5000 time steps after 10 000 time steps and each data point is averaged over 30 different realizations.

an evolutionary PDG. In this paper, we have introduced social welfare evaluation into the migration behavior of individuals and examined the different effects of three important SWFs that are widely studied in social science. By changing the interaction structure over time, different SWFs shape migration patterns and support the emergence and maintenance of cooperation in different ways.

In conclusion, we have studied the effects of social-welfare-based migration on the evolution of cooperation in a spatial PDG. Computer simulations of our model show that each SWF has a parameter range that supports the emergence and maintenance of cooperation. A key finding of this study is that the relative efficiency of an SWF for supporting cooperation is sensitive to the parameter values. For example, W_R will outperform the other two SWFs under high population densities, while W_U is optimal if there is no migration noise. The snapshots provide a plausible account of the different cooperation levels for different SWFs. W_U can outperform $W_{B\text{–}N}$ and W_R under a wide variety of conditions because the former SWF can help the population to form a robust cluster structure that can resist the invasion of defectors, especially in the presence of strategy noise. Because inequality aversion is an important property of the three discussed SWFs, this finding suggests that inequality aversion may play a significant role in the evolution of cooperation. Therefore, our work may be helpful in understanding the relationship between social preferences and cooperation in social systems.

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