The Impact of Heterogeneous Reputation Evaluation Laws on Cooperation Based on Net Logo

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Abstract. This paper explores the effect of three different reputation evaluation laws on the promotion of cooperation in the public goods game. Net Logo is used to analyze the main content. We find that tolerance is more conducive to promoting cooperation than rationality. Injecting more collectivism into a society is good for promoting cooperation, while an increase in rational people reduces this effect. The reorganization mechanism is partly beneficial to promote cooperation. In addition, when there are conflicts among agents due to the differences of reputation evaluation laws, the blind tolerance is not the best choice.

Keywords: Public goods game · Cooperation · Reputation · Values · Net logo

1 Introduction

Darwin's theory of evolution holds that selfish humans have no reason to incur costs to promote cooperation [1]. However, in real life, cooperation is ubiquitous. How to explain the emergence and maintenance of cooperation in human society has attracted the attention of many scholars. Evolutionary game theory provides a theoretical support for understanding the cooperative phenomenon and in particular, the public goods game (PGG) is adopted extensively to achieve this purpose [2]. PGG is a standard in experimental economics which is primarily used for analyzing human social coordination and cooperation [3]. So far, many mechanisms have been proposed to address this issue, including kin selection [4], punishment [5], reward [6], direct reciprocity [7] and indirect reciprocity [8]. Many studies have indicated that indirect reciprocity can stimulate cooperation by reputation [9].

However, in our daily life, people develop different values owing to different upbringing. The evaluator will make a reputational evaluation of the other's contribution based on his/her own values. The more haggling the values is, the more the evaluator concerns about the contribution of the one being evaluated. It indicates that different values have different effects on reputation evaluation. Based on this, we propose three laws of reputation evaluation by the three values, as follows: the law of fairness (LF), the law of equality

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(LE), and the law of need (LN). Under LF, the evaluator determines reputation based on the amount of contribution. Under LE, the evaluator determines reputation based on whether a contribution has occurred. Under LN, the evaluator determines reputation without consideration of contribution.

In this paper, we study the impact on the evolution of cooperation due to heterogeneous reputation evaluation laws. In Sect. 2, we will introduce the models. Section 3 shows the results of the simulations. Finally, we summarize the results.

2 Models

In our PGG model, individuals are arranged on a scale-free network randomly. We assume that each agent has k neighbors on average and joins k + 1 groups. Each agent i is allocated a random reputation value R. According to the three laws of reputation evaluation, we divide the agents into three types, LF-agent, LE-agent, LN-agent, who will adopt the three laws to evaluate reputation respectively. LF-agent can choose to cooperate or defect. LE-agent and LN-agent are both unconditional cooperators. Considering individual heterogeneity, cooperators can choose to donate any amount in a certain range. The payoff of agent i is calculated as follows:

$$P_i = \sum\nolimits_{j\in\Omega_i} p_i^j = \sum\nolimits_{j\in\Omega_i} \left(r\frac{c_j}{k_j + 1} - c_i \right) \tag{1}$$

where Ω_i represents the set of groups agent i participates in. c_i is used to represent the contribution of agent i, which is in [0, 10], c_j is the total contributions of the agents in group j. k_j is the number of neighbors of agent i in group j. r (>1) represents the synergy factor.

We assume that the agent's initial reputation R is randomly assigned in [0,1000]. After contributing, the contribution list will be published, which will provide information for evaluators to evaluate their own and other people's reputation. At step t, the reputation of the agent i consists of the following three parts: the reputation of round $R_i(t-1)$, the reputation evaluated by self $R_i'(t)$ and the reputation evaluated by others $R_i^*(t)$, where $R_i'(t)$ and $R_i^*(t)$ are allocated the weights α and β, respectively. The reputation updating formula is:

$$R_i(t) = R_i(t-1) + \alpha R_i^{'}(t) + \beta R_i^*(t), t \geq 1 \tag{2}$$

where $R_i^*(t)$ is the sum of $R_{iF}^*(t)$ and $R_{iE}^*(t)$. $R_{iF}^*(t)$ represents the reputation evaluated by LF-agents, $R_{iE}^*(t)$ represents the reputation evaluated by the LE-agents, $0 < \alpha, \beta < 1$ and $\alpha + \beta = 1$.

Everyone cares face, and reputation represents one's face. If one's reputation was less than the reputation threshold (R_T), he/she would feel ashamed. Then he/she will adjust the contribution to improve his/her reputation.

When $R_i(t) \geq R_T$, the LF-agents are rational payoff-driven, and they attempt to maximize returns by randomly imitating a neighbor's strategy in last round with the following probability:

$$W(S_i \leftarrow S_j) = \frac{1}{1 + exp[(p_i - p_j)/\phi]} \tag{3}$$

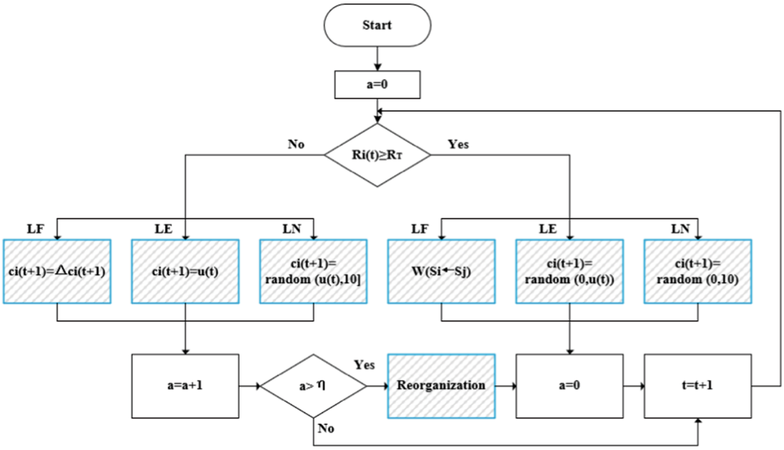

Fig. 1. The circulatory process of decision-making of different agents.

Where ϕ represents the amplitude of the ambient noise. S_i and S_j denote strategies representing agent i and neighbor j, respectively. p_i-p_j is the difference between the payoffs of agent i and neighbor j.

Since the LE-agents and the LN-agents are unconditional cooperator, they will donate in every round. The LE-agent i will contribute a random value in (0, u(t)) at step t + 1, where u(t) represents the average level of the contribution at step t. LN-agents are more rigorous to themselves than LE-agents, so their average level of contributions is higher than LE-agents'. The LN-agent i will choose a random value in (0,10) as his/her contribution at step t + 1.

When $R_i(t) < R_T$, agents will try their best to increase their reputation to meet R_T. Therefore, the LF-agent i will calculate the required contribution amount $\Delta c_i(t + 1)$ at step t + 1 according to R_T and Eq. (2). The calculation formula is as follows:

$$\Delta c_i(t+1) = \frac{R_T - R_i(t-1) - \beta * 10}{(\alpha + \beta) * 10} + u(t) \tag{4}$$

It should be noted that each agent can contribute up to 10 in each round. So, when $\Delta c_i(t + 1) > 10$, let $\Delta c_i(t + 1) = 10$, otherwise the value of $\Delta c_i(t + 1)$ does not change.

The LE-agents think that whether to contribute is more important than how much to contribute. When their own reputation is less than RT, they will donate the minimum amount needed to enhance their reputation. So the LE-agent i contribute u(t) in round t + 1. The LN-agents are the most self-critical of these three type agents. Thus, the LN-agent i will contribute a random value in (u(t),10) in round t + 1.

We assume that when an agent fails to reach the threshold for consecutive η times, he will be rejected by his neighbors. And the agent will leave the current group and join a new group again, it will be explain in Sect. 2.2. The decision making process of a random selected agent i in the model is shown in the Fig. 1.

2.1 Heterogeneous Reputation Evaluation Laws

According to the different values, we set three reputation evaluation laws. To better conform the reality, we assume that people not only evaluate others, but also evaluate themselves. Three reputation evaluation laws are introduced in the following:

The law of fairness (LF): LF-agents adhere to the principle of "more work more pay, less work less pay". Under the law of fairness, LF-agents evaluate their own and others' reputation by the same standard: the amount of contributions. They think that if you contribute more than average, your reputation will increase and if you contribute less than average, your reputation will decrease. The LF-agent's formula for evaluating own and other's reputation is as follows:

$$\begin{cases} R'_{iF}(t) = (c_i(t) - u(t)) * 10 \\ R'_{iF\to j}(t) = (c_j(t) - u(t)) * 10 \end{cases} \tag{5}$$

Where $R'_{iF}(t)$ is LF-agent i's assessment of his/her own reputation. $R'_{iF\to j}(t)$ is LF-agent i's assessment of the randomly selected agent j's reputation. $c_i(t)$, $c_j(t)$represents the contribution of agent i and j at step t, respectively. u(t) is the average amount of contributions of all agents at step t.

The law of equality (LE): LE-agents consider that it doesn't matter how much you contribute, but whether you contribute. And they judge themselves more strictly than others. Under the law of equality, when evaluating others, LE-agents will increase the reputation by 10 as long as the evaluee makes contribution. On the contrary, if the evaluee's contribution is 0, his/her reputation will be decreased by 10. When evaluating themselves, LE-agents require their contributions to surpass the average level u(t). The LE-agent's formula for evaluating own and other's reputation is as follows:

$$R'_{iE}(t) = \begin{cases} 10 c_i(t) \geq u(t) \\ -10 c_i(t) < u(t) \end{cases} \tag{6}$$

$$R'_{iE\to j}(t) = \begin{cases} 10 c_j(t) > 0 \\ -10 c_j(t) \leq 0 \end{cases} \tag{7}$$

Where $R'_{iE}(t)$ is LE-agent i's assessment of his/her own reputation. $R'_{iE\to j}(t)$ is LE-agent i's assessment of the randomly selected agent j's reputation.

The law of need (LN): The LN-agents believe that the allocation of resources should meet the reasonable needs of the recipient. So the LN-agents don't care if others contribute. Under the law of need, LN-agents will not evaluate others' reputation. When evaluating themselves, the LN-agents judge themselves more strictly than LE-agents. They will require their contributions to be above the average level, and their reputation can only be increased by 5. The formula for calculating reputation is as follows:

$$R'_{iN}(t) = \begin{cases} 5, c_i(t) \geq u(t) \\ -10, c_i(t) < u(t) \end{cases} \tag{8}$$

where $R'_{iN}(t)$ is LN-agent's assessment of his/her own reputation.

2.2 Reorganization Mechanism

In most cases, when an agent's behavior is always inconsistent with the group, he/she will become more and more alienated with neighbors. And it will also cause this agent to break away from the present group, and choose to join a new group that is more suitable for him. So we assume that when agent's reputation is lower than R_T for consecutive rounds, the neighbors will discuss the agent through gossip and other methods, which will let this agent feel faceless. And this agent will disconnect from his/her present neighbors and establish a new connection with an agent who is not the previous neighbor. We assume that an agent has five ways to establish a new connection with another one after leaving the present group, namely, link 1: randomly select an agent, link 2: select an agent with the closest distance, link 3: select an agent with the closest reputation, link 4: select an agent with the closest contribution amount, link 5: choose an agent with the same reputation evaluation law. Through five ways, the agent joins a new group but reputation evaluation law does not change.

3 Simulation Results

To reduce MCS stochastic errors, a large number of simulations are performed to investigate the evolutionary process on a scale-free network. Each data point is obtained by 20 independent runs with at least 10000 steps. At first, to better conform the real society, the fractions of LF-agents(f1), LE-agents(f2), LN-agents(f3) are 80%, 10%, 10% respectively. Other parameters are set to be $N = 400$, $K = 4$, $r = 2$, $\phi = 0.01$, $\eta = 4$, $\alpha = 0.5$, $\beta = 0.5$, $R_T = 200$. Reorganization mechanism is link 1. To better verify the effect of the LE and the LN on cooperation, all LF-agents are set to be defectors at the beginning. When one of the parameters is discussed, others remain stationary. The simulation results are all to reach full cooperation, so we mainly discuss the impact of different reputation evaluation laws through Gs and Ts. Gs is the generations to achieve full cooperation and Ts refers to the total contributions under equilibrium.

Firstly, the population structure is discussed in this part. The fraction of LF-agents is changed from 80% to 95%, while LE-agents and LN-agents always account for half of the rest. Figure 2(a) shows the process of evolution of cooperation frequency for different population structure. LE-agents and LN-agents are more tolerant of the amount of contributions than LF-agents. Thus, the result illustrates that tolerance is more conducive to promoting cooperation than rationality in a society where indirect reciprocity works. It can be seen from Fig. 2(a) that as f1 increases, the curve gradually moves to the right before reaching equilibrium, which means it needs more generations to achieve cooperation of all. Figure 2(b) shows the process of total contributions for different population structure. It shows that population structure can't influence the sum of contributions. We can see that all curves are leveled at similar heights in Fig. 2(b).

Secondly, we discuss the influence of social collectivism and individualism on cooperation by α and β. α and β represent self-evaluation weight and other-evaluation weight respectively. Therefore, we assume that when $\alpha > \beta$ the group is more inclined to individualism, when $\alpha < \beta$ the group is more inclined to collectivism. In Fig. 3, we can see that as α enlarges, more generations are need to achieve full cooperation, it means collectivism is more conducive to promote cooperation. Besides, it can be seen that with

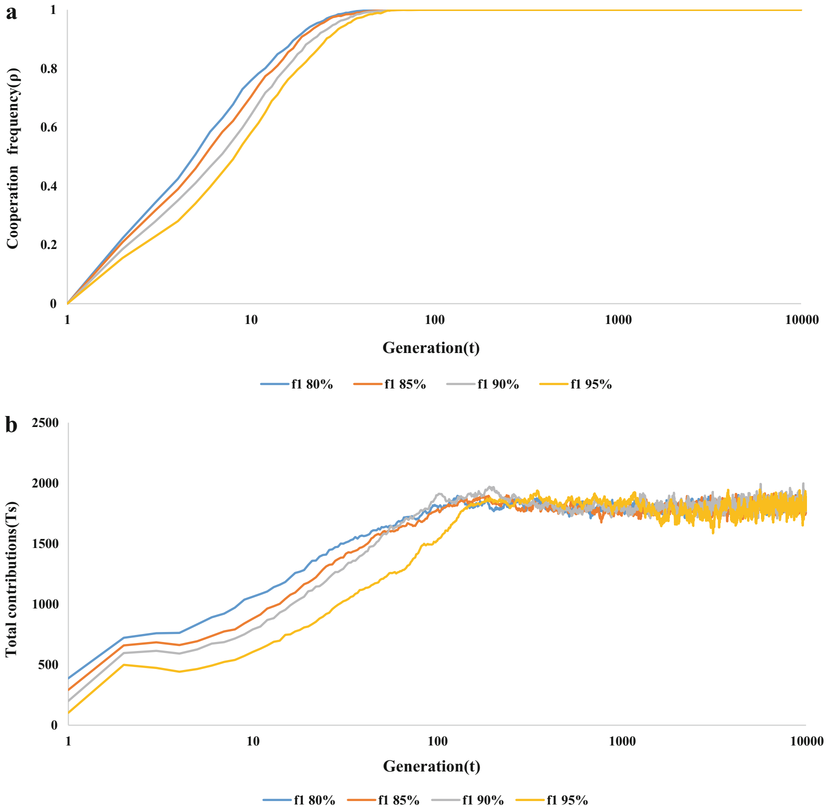

Fig. 2. The evolution results of the cooperation frequency (ρ) and the total contributions (Ts)

the increase in the fraction of rational LF-agent, the generations to equilibrium is enlarging although the change of α is the same. Thus we can conclude that injecting more collectivism into the society is conducive to promoting cooperation, while the increase of rational people will reduce this effect.

Next, we will discuss the impact of reorganization mechanism on promoting cooperation in Fig. 4. On one hand, we can conclude that except link 3 most reorganization mechanisms can promote the speed of getting full cooperation. By comparing all blue bars with the white one in Fig. 4(a), we can find that except link 3, other blue bars are shorter than the white one. Besides, it can be seen that the standard deviations under each conditions are similar, which means the performances are steady. On the another hand, we conclude that reorganization mechanisms will not decrease the total contributions and link 3 can increase total contributions significantly. In Fig. 4(b), we can see that the bar of link 3 is taller than the white one obviously, other blue bars are about the same height as the white one. Then the standard deviations of link 5 and link 3 are bigger than others. Considering the large base of link 3, we think the big standard deviation don't diminish its positive effect. Therefore, link 5 is recognized as the worst performer in

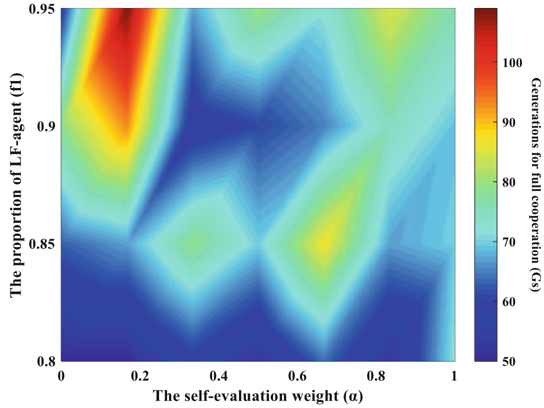

Fig. 3. Represents the generations for full cooperation Gs under different f1 and α.

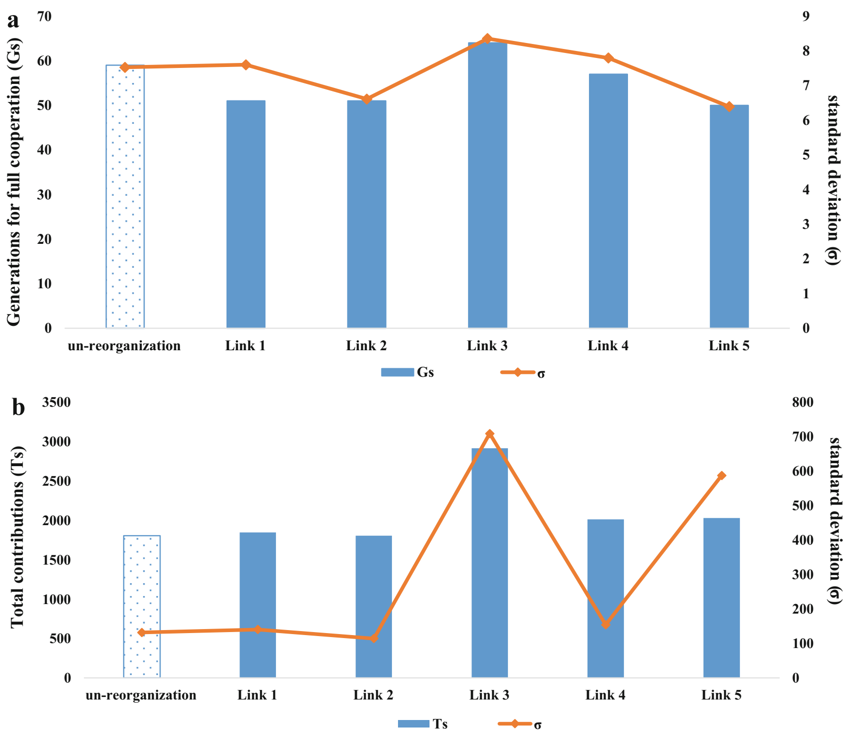

Fig. 4. Shows the generations for full cooperation (Gs) and total contributions (Ts).

promoting contributions. Based on the analysis, it can be found that the reorganization mechanism is conducive to promoting cooperation to a certain extent.

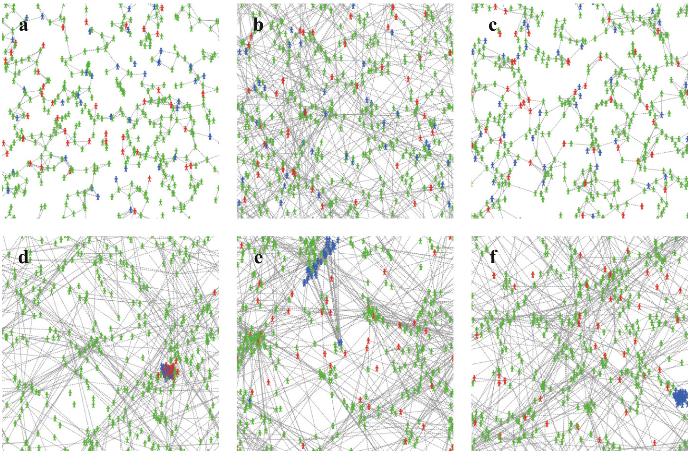

Fig. 5. This is the snapshot of the conditions of un-reorganization (Fig. 5(a)), link 1(Fig. 5(b)), link 2(Fig. 5(c)), link 3(Fig. 5(d)), link 4(Fig. 5(e)) and link 5(Fig. 5(f)). The green agents are the LF-agents. The blue agents are the LE-agents. The red agents are the LN-agents.

In order to further understand how the reorganization mechanisms affect the behavior, we will analyze the space snapshot under the un-reorganization and five reorganization mechanisms. In Fig. 5(a)-(c) agents are distributed randomly, but in Fig. 5(d)-(f) we find some interesting clustering phenomena. In Fig. 5(d) LE-agents and LN-agents cluster together in a circle. According to Fig. 4, we can conclude that encouraging the gathering of different types of unconditional cooperators can promote the amount of contribution. In Fig. 5(e) and (f) the LE-agents cluster together in a strip and circle respectively. Considering Fig. 4, it can be concluded that clustering in a strip is more conducive to fundraising stably than clustering in a circle.

Next, we will consider the role of η. η represents the degree of tolerance of the neighbors to the agent. Figure 6 shows the generations to achieve full cooperation (Gs) and total contributions (Ts) under different η. In Fig. 6, it is found that as η enlarges, the orange line moves up and the blue line moves down, which reduces the cooperation efficiency. Therefore, when there are conflicts among agents due to the different reputation evaluation laws, the blind tolerance is not the best choice.

Finally, the effects of the synergy factor r and the noise figure ϕ will be discussed. Figure 7(a) and (b) show the equilibrium results of the generations to achieve full cooperation (Gs) and total contribution (Ts) for different r and ϕ. In Fig. 7(a), both orange and blue lines fluctuate in a narrow range. In Fig. 7(b), we can see that the orange line and blue line move downward slightly, and the fluctuations of them are very little. Based on these data, we can conclude that the changes in r and ϕ have an effect on the model, but the magnitude of the effect is not obvious.

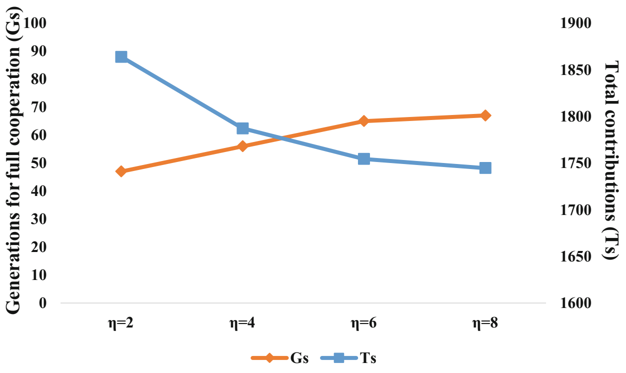

Fig. 6. This is the results of the generations for full cooperation and the total contributions.

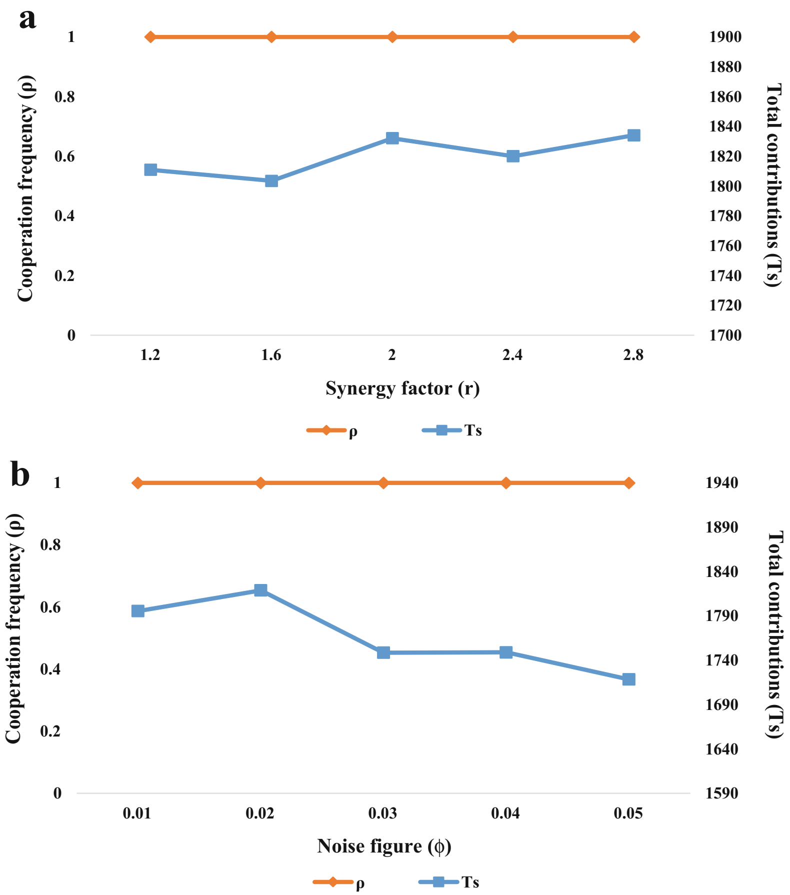

Fig. 7. Shows the equilibrium results of the Gs and the Ts.

4 Conclusion

Reputation evaluation laws have heterogeneity. Therefore, we propose three reputation evaluation laws, namely the law of fairness (LF), the law of equality (LE) and the law of need (LN). At the same time, we set up reorganization mechanism. Through a large number of experimental studies, we come to the following conclusions: (i) Tolerance is more beneficial to promoting cooperation than rationality in a society. (ii) Injecting more collectivism into the society is conducive to promoting cooperation, while the increase of rational people will reduce this effect. (iii) The reorganization mechanism is partly conducive to promoting cooperation. (iv) When there are conflicts among agents due to the differences of reputation evaluation laws, the blind tolerance is not the best choice. To sum up, in this paper we have investigated the influence of heterogeneous reputation evaluation laws on cooperation in PGG. Moreover, we hope the research can provide a new idea for others to study reputation mechanism to cooperation.

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