

## Supplementary Information for

### Emergence of Communities and Diversity in Social Networks

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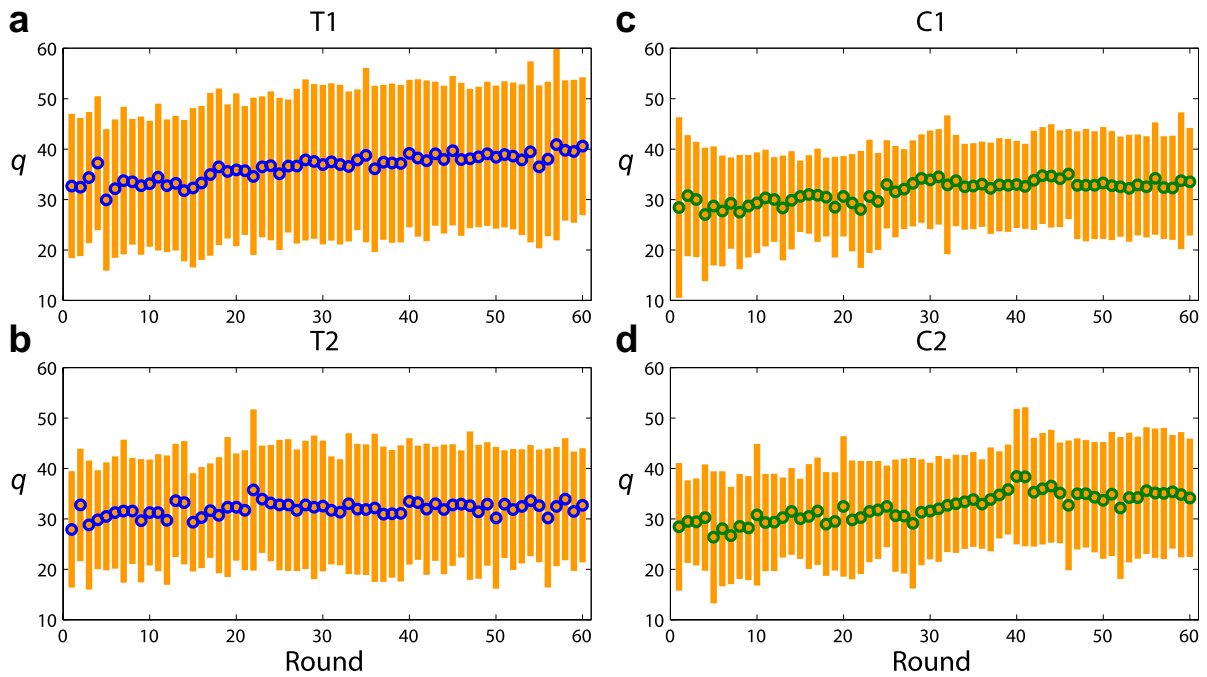
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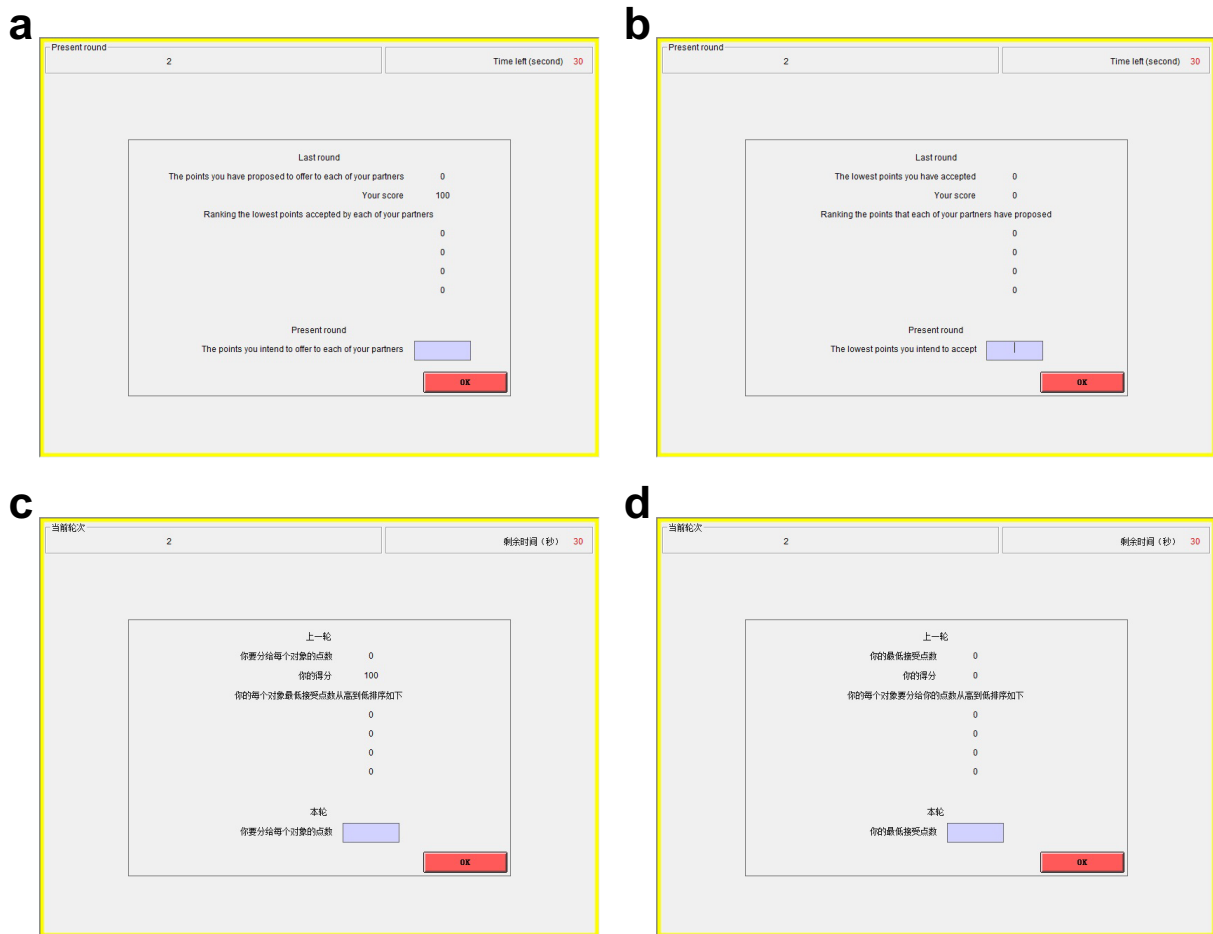
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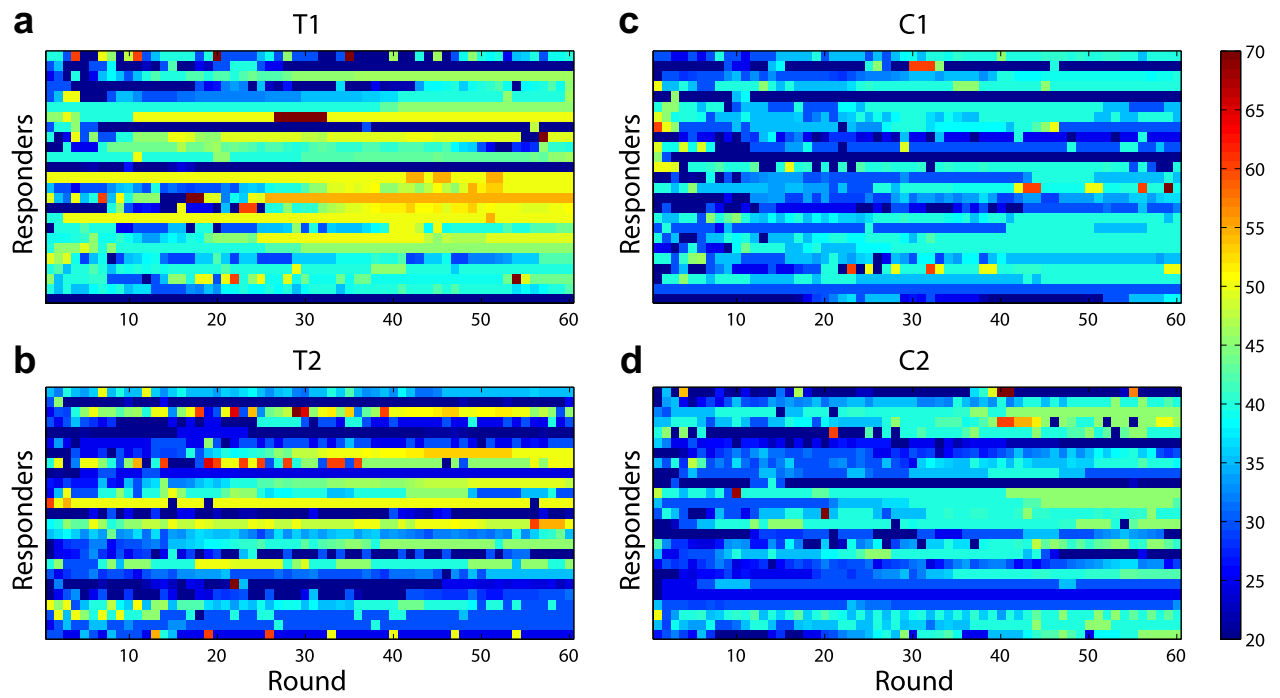
# 1 Supplementary Figures



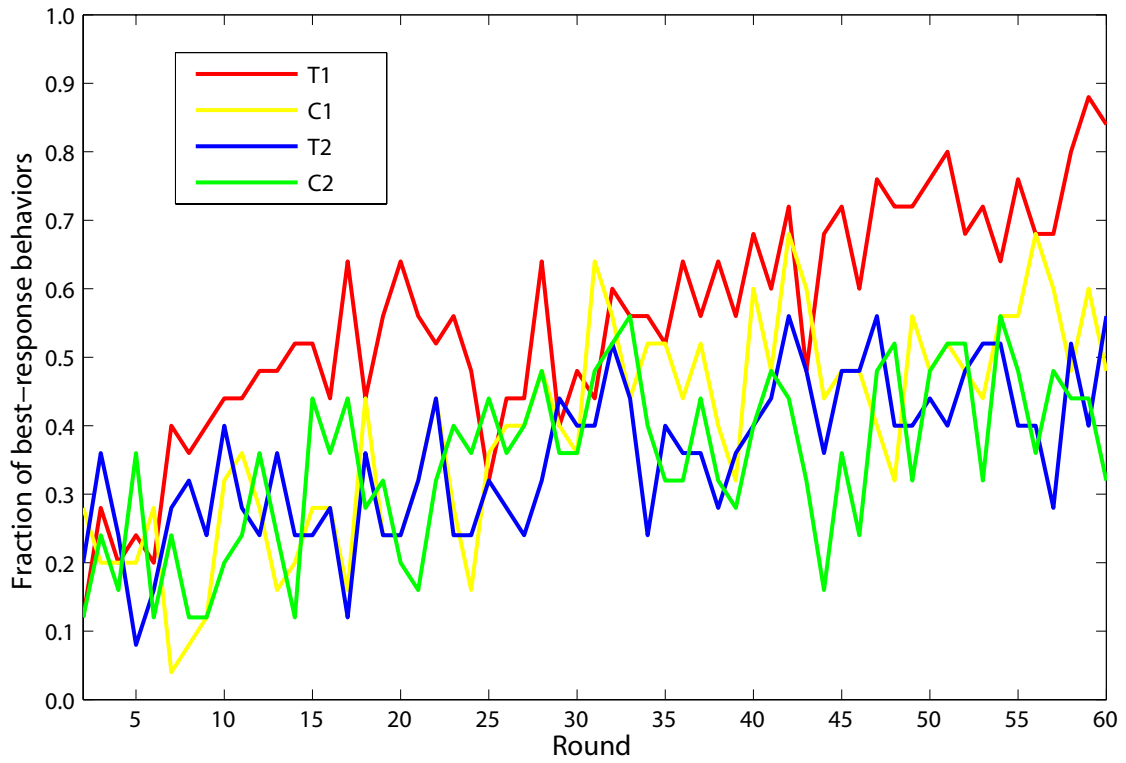
**Supplementary Figure S1: Evolution of the minimum acceptance level  $q$  in the treatment and control groups.** (a-d) The evolution of  $q$  in the two treatment groups, T1 (a) and T2 (b), and the two control groups, C1 (c) and C2 (d), respectively. The mean value and the standard deviation (i.e., the square root of the variance) of  $q$  in each of the 60 rounds are denoted by circles and column bars, respectively. The average value of  $q$  in T1 is slightly higher than the other groups, and  $q$  in both the treatment and control groups displays big standard deviations and little difference is observed between them.



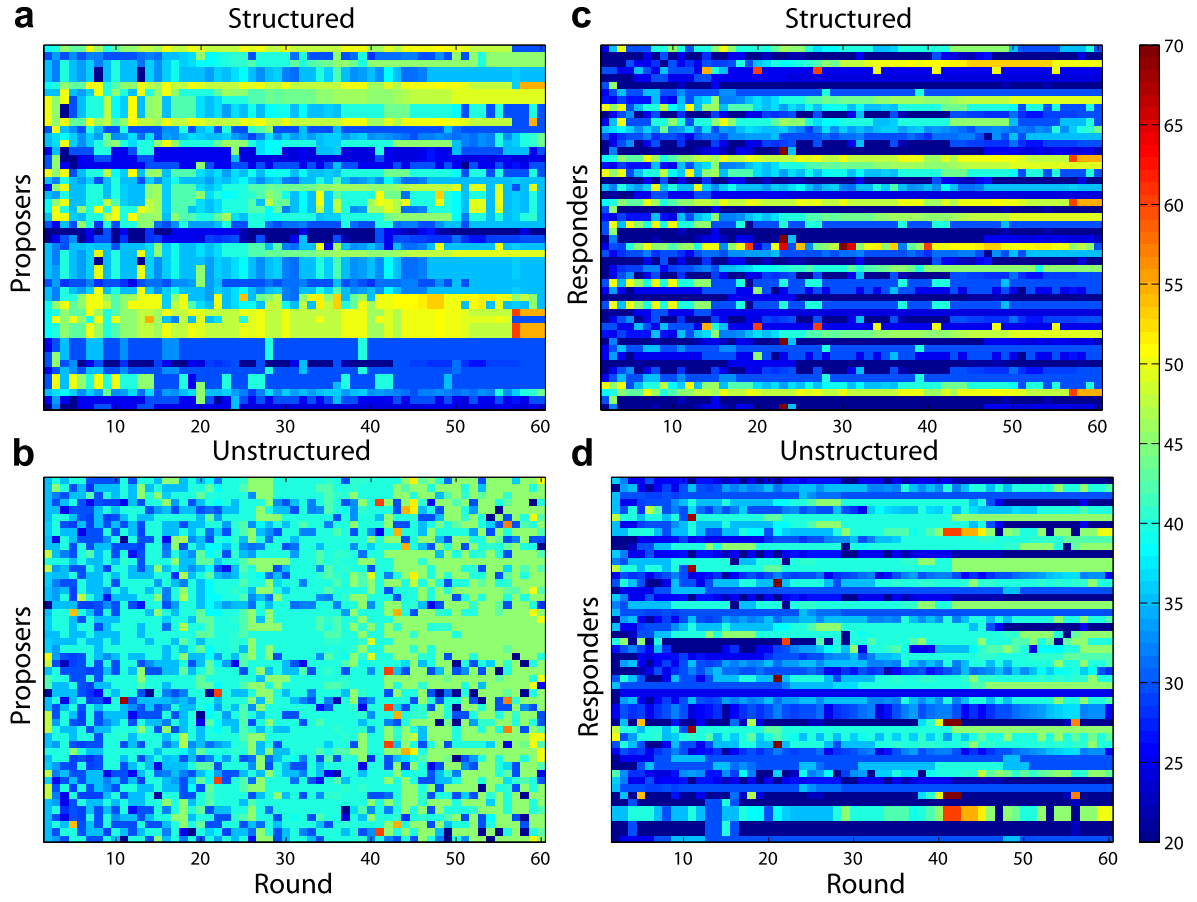
**Supplementary Figure S2: Screen shots of experimental interfaces.** (a,b) Interface of proposers (a) and responders (b) in English. (c,d) Interface of proposers (c) and responders (d) in Chinese. We used the two interfaces in Chinese in the experiments and the English versions are direct translations of the Chinese versions.



**Supplementary Figure S3: Spatio-temporal patterns of responders.** (a,b) Spatio-temporal patterns of the responders' minimum acceptance level  $q$  in the two treatment groups T1 (a) and T2 (b). (c,d) Spatio-temporal patterns of the responders' minimum acceptance level  $q$  in the two control groups C1 (c) and C2 (d). The color bar represents the value of  $q$ .



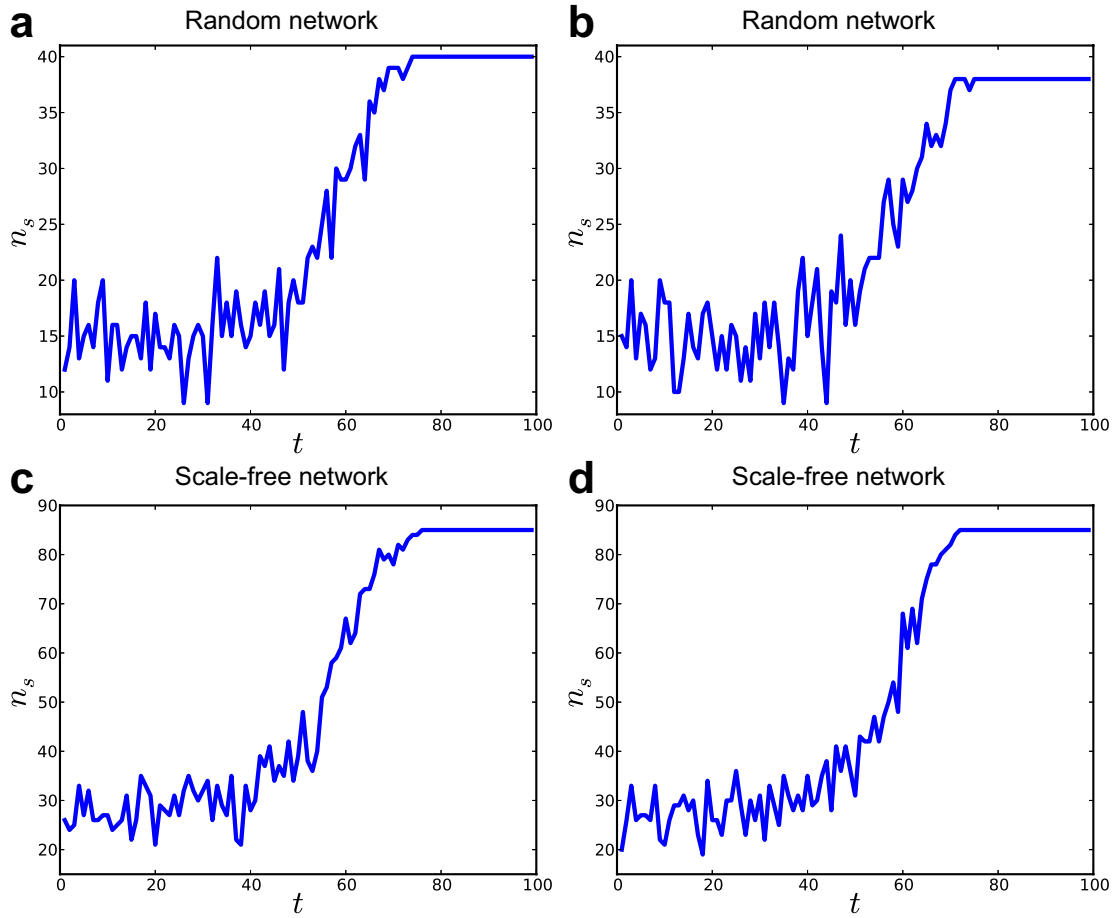
**Supplementary Figure S4: The fraction of rational proposers with best-response strategy.** The frequencies of best-response strategy from round 2 to round 60 in T1 (red), C1 (yellow), T2 (blue) and C2 (green). In round 2, there are only 18 rational proposers in the 100 proposers (3 in T1, 7 in C1, 5 in T2 and 3 in C2). In contrast, in round 60, there are 55 rational proposers (21 in T1, 12 in C1, 14 in T2 and 8 in C2).



**Supplementary Figure S5: Spatio-temporal patterns of proposers and responders in scale-free networks.** (a) Spatio-temporal patterns of the proposers' offers  $p$  in structured scale-free bipartite network and clear local clusters are observed. (b) Spatio-temporal patterns of the proposers' offers  $p$  in unstructured scale-free bipartite network and a single homogeneous community of proposers arises. (c,d) Spatio-temporal patterns of the responders' minimum acceptance level  $q$  in structured (c) and unstructured (d) scale-free bipartite networks, respectively. Structured and unstructured populations correspond to virtual experiments with static scale-free networks and constantly changing networks with the same node degrees as their counterparts with fixed structures. Network parameters are  $\langle k \rangle = 4$  and  $N = 100$  (i.e., 50 proposers and 50 responders). The color bar represents the value of  $p$  and  $q$ .



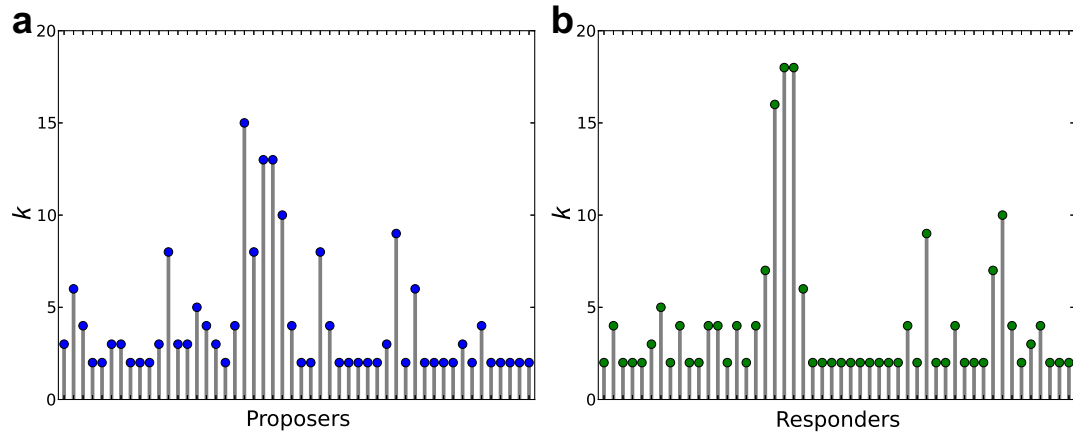
**Supplementary Figure S6: Photo of the computer lab.** This photo shows a part of the laboratory. White cardboard dividers are used to avoid participants glancing others' screens. Participants can play the game in a quiet environment.



**Supplementary Figure S7: Optimizing configuration energy using simulated annealing algorithm.**

(a,b) Optimizing spatial sequence of proposers (a) and responders (b) in the random bipartite network in T2, respectively. (c,d) Optimizing spatial sequence of proposers (c) and responders (d) in the scale-free bipartite network (used in Supplementary Fig. S5 with  $\langle k \rangle = 4$  and  $N = 100$ ), respectively. Energy  $n_s$  is defined as the sum of the number of common neighbors of all pairs of adjacent nodes.





**Supplementary Figure S8: Sequence of node degrees versus spatial sequence in a scale-free network.** (a,b) Node degrees  $k$  of proposers (a) and responders (b) in the optimized spatial sequence. We see that high-degree nodes tend to gather together for both proposers and responders, because the number of common neighbors of high-degree nodes is larger than that of shared with other nodes. The scale-free bipartite network is the same as used in Supplementary Fig. S5.

## 2 Supplementary Tables

**Supplementary Table S1: Statistic results for inherent diversity of responders’ behaviors.** Standard deviation between responders’ minimum acceptance levels,  $SM(q)$ , and mean value of the standard deviation within responders’ minimum acceptance levels over 60 rounds,  $MS(q)$ , in the two control experiments and two treatments. The results show that the standard deviation between the behaviors of responders is larger than the standard deviation within their behaviors. This implies that the behaviors of responders have inherent diversity.

|    | $SM(q)$ | $MS(q)$ |
|----|---------|---------|
| T1 | 12.72   | 7.02    |
| C1 | 7.61    | 6.39    |
| T2 | 9.93    | 6.49    |
| C2 | 7.87    | 7.20    |

**Supplementary Table S2: Mean values and standard deviation of  $p$  in “shuffle” games.** Similarly as Table I,  $mean(p)$  and  $std(p)$  represent the mean value and the standard deviation of offers of all proposers, respectively.  $std(p)$  in shuffle games with network structures are significantly higher than that in shuffle games without with random interactions.

|                       | $mean(p)$ | $std(p)$ |
|-----------------------|-----------|----------|
| C1 on T1<br>network   | 46.36     | 4.75     |
| T1 without<br>network | 39.26     | 0.58     |
| C2 on T2<br>network   | 40.11     | 7.64     |
| T2 without<br>network | 40.08     | 1.17     |

**Supplementary Table S3: The mean value and standard deviation of proposers' offers in regular bipartite networks and random bipartite networks with different ratios between proposers and responders.**  $N_P$  and  $N_R$  represent the number of proposers and responders, respectively.  $\langle k \rangle_P$  and  $\langle k \rangle_R$  represent the average nodal degree of proposers and responders, respectively. In regular bipartite networks, all proposers (resp. responders) have the same degree, while in random bipartite networks, their degrees can be different.  $\text{Mean}(p)$  and  $\text{std}(p)$  represent the mean value and the standard deviation of offers of all proposers, in which a proposers offer is taken as the average of his/her offers  $p$  from round 2 to round 60, respectively. Structured and unstructured correspond to virtual experiments with static networks and constantly changing networks with the same node degrees as their counterpart with fixed structures. The results are calculated by implementing 1000 independent realizations.

| $N_P$ | $N_R$ | $\langle k \rangle_P$ | $\langle k \rangle_R$ | mean( $p$ )                            |             | std( $p$ )                             |           |
|-------|-------|-----------------------|-----------------------|--|-------------|--|-----------|
|       |       |                       |                       | Regular<br>(Structured / unstructured) | Random      | Regular<br>(Structured / unstructured) | Random    |
| 50    | 25    | 4                     | 8                     | 42.57/42.67                            | 42.16/42.02 | 4.23/0.83                              | 4.80/1.79 |
| 75    | 25    | 3                     | 9                     | 41.50/41.53                            | 40.96/40.94 | 5.00/0.97                              | 5.43/1.80 |
| 25    | 50    | 8                     | 4                     | 44.12/44/11                            | 44.06/44.02 | 2.98/0.64                              | 3.19/1.06 |
| 25    | 75    | 9                     | 3                     | 44.40/44.37                            | 44.31/44.27 | 2.86/0.62                              | 3.14/0.95 |

### 3 Supplementary Note 1: Optimization method for ordering participants in complex networks

Figure 3 shows the allocated spatial locations of the participants, which were based exclusively on the network topology. Our goal is to put the participants with the largest number of common neighbors together in a double ring. In the regular bipartite network we accomplish this goal by following the natural periodic structural properties, as shown in Fig. 3(A). Note that spatially adjacent participants have the largest number of common neighbors. In the random bipartite network, however, it is difficult to determine adjacent subjects by their common neighbors because of the complex topology. To address this problem, we use a simulated annealing algorithm to yield a best configuration. We define an energy function  $n_s$  in terms of the number of common neighbors of all pairs of immediately adjacent nodes,  $n_s \equiv \sum_{i=1}^{N/2-1} n_{i,i+1} + n_{N/2,1}$  (where  $N$  is the number of nodes,  $N/2$  the total number of each type of node, and  $n_{i,j}$  the number of common neighbors between  $i$  and  $j$ ) and consider the periodic boundary condition.

In order to achieve the maximum energy that corresponds to the optimal spatial configuration in which the sum of shared neighbors between adjacent nodes are maximized, we initially assign a random spatial order for each type of node. Specifically, at step  $t + 1$  we randomly pick two nodes in the sequence and exchange their locations. If the energy is increased in a new configuration, we accept it. If it is not, we accept a worse configuration with a small probability  $\exp\{[n_s(t + 1) - n_s(t)]/T(t)\}$  if  $n_s(t + 1) < n_s(t)$ , where  $T$  is the temperature, and we set  $T = 300 \times 0.9^t$ . As  $t$  increases, temperature  $T$  eventually approaches zero. The simulated annealing algorithm allows the energy to escape from local maxima and approach global maxima. We implement the optimization algorithm for both proposers and responders and find that their maximum energies are 40 and 38, respectively. We similarly obtain an optimal spatial sequence of proposers and responders in a scale-free network (see Supplementary Fig. S7). Note that high-degree nodes gather together, as shown in Supplementary Fig. S8. Note also that the given sequence of nodes with periodic boundary conditions do not rely on participant behavior but are determined by topology. The presence of local agreement among topological-based adjacent participants indicates the significant role of network structure in the evolution of the UG.

### 4 Supplementary Note 2: Evaluating the rationality of participants

We used a rigorous test to identify whether participants were rational. Participants who used the best strategy in response to the behaviors of their neighbors in the previous round were considered rational. The best strategy for rational responders would have been to accept all proposals from their neighbors. We found that only  $\approx 2\%$  of the responders in either the structured or unstructured UG were rational in every round. The rest rejected “unfair” proposals. The best strategy for rational proposers in each round was to offer the amount that maximizes payoff, keeping in mind the minimum acceptance levels demonstrated by neighbors in the previous round [1, 2]. For a proposer with  $k$  neighbors whose minimum

acceptance levels in the previous round were respectively  $q_1, \dots, q_k$  (with  $q_1 < \dots < q_k$ ), the best strategy was  $p = \operatorname{argmax}_{q_i} \{i \times (100 - q_i)/k\}$ , where  $i \times (100 - q_i)/k$  was the payoff if the proposers offered  $q_i$ . We found that the faction of rational proposers gradually increased and eventually exceeded half of population in all groups (see Supplementary Fig. S4). Our definition of rational behaviors was rigorous, and we found that the proportion of rational proposers was high.

## 5 Supplementary Note 3: Experimental Setup

The experiment was carried out in the computer labs of Beijing Normal University over a two-day period. On the first day T1 and C1 were conducted, and on the second day T2 and C2. All 200 participants were freshmen and sophomores recruited from Beijing Normal University who were not enrolled in classes studying game theory and economics. We built the experimental platform by using z-Tree [3]. The interactions were executed via computer and were anonymous. Cardboard dividers ensured that the students could not see each other (see Supplementary Fig. S6). Players were not allowed to communicate. They were allowed to ask questions before the experiment began but not during the experiment.

Before starting the experiment, we provided a 30-minute explanation of the game to all participants. This included the rules of the game, the purpose of the game, and the feedback information in the computer. All players in each session were given the same instructions (in Chinese). (For a translation of the instructions, see Supplementary Note 3.) To ensure that all participants fully understood the game, we set aside a 15-minute period for five practice rounds before beginning the formal experiment. The formal experiment lasted approximately 45 minutes and each round was time-limited. Players knew that if they did not make a decision within 30 seconds, they would be assigned the decision from their previous round. Since the players had familiarized themselves with the game during the practice rounds, this happened only 546 times in 12000 decisions (in T1, 85 times in 3000 decisions; in C1, 282 times in 3000 decisions; in T2, 151 times in 3000 decisions; and in C2, 28 times in 3000 decisions). After the experiment the score of each participant obtained in the formal experiment was converted to Chinese Yuan at a ratio of 50 : 1. The payoff plus 20 Yuan was their total income. The average income was 71.85 Yuan (with a minimum of 45 and a maximum of 102). The T1 average income was 71.56 Yuan (minimum 52, maximum 81), the C1 was 74.30 Yuan (minimum 57, maximum 89), the T2 was 69.70 Yuan (minimum 45, maximum 102), and the C2 was 71.84 (minimum 52, maximum 86). To keep the comparison unbiased, all results were calculated using data in 1–60 rounds.

## 6 Supplementary Note 4: Experimental Instructions

### Instructions:

Welcome and thank you for participating in this experiment. Please read these instructions carefully. If you have any questions please raise your hand. One of the experimenters will come to you and answer your questions. From now on communication with other participants is not allowed. Please switch off

your mobile phones.

### **Instruction for T1**

#### *1. The basic game:*

There are two types of players, Player 1 and Player 2. Player 1 makes an offer on how to split 100 tokens. Player 2 can decide whether to accept or reject the offer made by Player 1. If Player 2 accepts, then the tokens are divided as proposed by Player 1. If Player 2 rejects the offer both Players receive 0.

#### *2. Rules of the game*

(1) At the beginning of the experiment, your role will be determined randomly. You will be randomly matched with 4 other participants (your partners) who play the other role. Your role and your partners will not change during the experiment.

(2) In each round, Player 1 will play the basic game with their partners by inputting a value  $p$ , which means giving  $p$  tokens to each partner.

(3) In each round, Player 2 can decide whether to accept each of his/her partner's offer by inputting a value  $q$ , which means offer no less than  $q$  will be accepted.

(4) After all the participants have submitted their values, the system will calculate your score. Your score = (your tokens)/(number of partners).

#### *3. A Player 1 example*

(1) Player 1 has four Player 2 partners.

(2) Suppose Player 1 gives  $p$  tokens to each partner, and the acceptance levels of the four partners are  $q_1 > q_2 > q_3 > q_4$ .

(3) If  $q_1 > q_2 > p \geq q_3 > q_4$ , then two partners ( $q_3$  and  $q_4$ ) accept the offer. Player 1 gets  $(200 - 2p)$  tokens and the score is  $(200 - 2p)/4$  (4 is the number of partners).

#### *4. A Player 2 example*

(1) Player 2 has four Player 1 partners.

(2) Suppose the acceptance level of Player 2 is  $q$ , and the offers made by the four partners are  $p_1 > p_2 > p_3 > p_4$ .

(3) If  $p_1 > p_2 > q \geq p_3 > p_4$ , then two offers ( $p_1$  and  $p_2$ ) are accepted. Player 2 gets  $(p_1 + p_2)$  tokens and the score is  $(p_1 + p_2)/4$  (4 is the number of partners).

#### *5. Payment*

Your total income = show up fee 20 Yuan+ your total score  $\times 0.02$  Yuan.

### **Instruction for C1**

#### *2. Rules of the game*

(1) At the beginning of the experiment, your role will be determined randomly and will not change during the experiment.

(2) At the beginning of each round, you will be randomly matched with four other participants (your partners) who will play the other role.

(3) In each round, Player 1 will play the basic game with each of their partners by inputting a value  $p$ , which means giving  $p$  tokens to each partner.

(4) In each round, Player 2 can decide whether to accept each of his/her partner's offer by inputting a value  $q$ , which means no offer less than  $q$  will be accepted.

(5) After all the participants have submitted their value, the system will calculate your score. Your score = (your tokens)/(number of partners).

[The rest of the parts are the same as T1.]

### **Instruction for T2**

#### *2. Rules of the game*

(1) At the beginning of the experiment, your role will be determined randomly. You will be randomly matched with other participants (your partners) who will play the other role. Your role and your partners will not change during the experiment.

(2) In each round, Player 1 will play the basic game with each of their partners by inputting a value  $p$ , which means giving  $p$  tokens to each partner.

(3) In each round, Player 2 can decide whether to accept each of his/her partner's offer by inputting a value  $q$ , which means no offer less than  $q$  will be accepted.

(4) After all the participants have submitted their value, the system will calculate your score. Your score = (your tokens)/(number of partners).

[The rest of the parts are the same as T1.]

### **Instruction for C2**

#### *2. Rules of the game*

(1) At the beginning of the experiment, your role will be determined randomly and will not change during the experiment.

(2) At the beginning of each round, you will be randomly matched with some other participants (your partners) who will play the other role. The number of your partners will not change during the experiment.

(3) In each round, Player 1 will play the basic game with each of their partners by inputting a value  $p$ , which means giving  $p$  tokens to each partner.

(4) In each round, Player 2 can decide whether to accept each of his/her partner's offer by inputting a value  $q$ , which means no offer less than  $q$  will be accepted.

(5) After all the participants have submitted their value, the system will calculate your score. Your score = (your tokens)/(number of partners).

[The rest of the parts are the same as T1.]

## 7 Supplementary Note 5: Some comments

Although we realize that the network size in our experiments is relatively small, the experimental findings, shuffle tests, and virtual games on scale-free networks indicate that network size has little influence on communities and social diversity. Because we have discovered that the communities are formed by locally constrained interactions, increasing network size will not affect local interactions, which will resemble those in small networks. That is why we have not conducted larger-scale experiments than the current 50-participant groups.

Regarding the unchanging single role of each participant in our experiments, we do not know whether the experimental findings can be extended to the dual-role scenario that has been the focus of many theoretical studies [4, 5, 6, 7, 8, 9], but we used a single role for each subject for two reasons.

First, dual identities could confuse a participant without any previous knowledge of the UG, especially after several rounds. Second, in dual-role experiments there is a time-out problem. Because subjects would need sufficient time to make two different kinds of decision based on massive feedback information from the previous round—which would include all of their neighbors' payoffs, offers, and minimum acceptance levels and their own payoffs, offers, and minimum acceptance levels—it would not generate useful results. The careful design of the experiment needs to simplify subject decision-making, avoid subject confusion, and reduce latency time in each round. That is why we have used the simplified single-role version. The single-role UG is able to provide insight into the behaviors of both proposers and responders when they engage in multiple games simultaneously. The knowledge gained is important not only for making predictions but also for providing expectations associated with subsequent dual-role UG experiments. Our work is thus an initial experimental attempt to eventually understand fairness and altruism in populations with multiple local interactions.



## 8 Supplementary References

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