Emergence of communities and diversity in social networks

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Communities are common in complex networks and play a significant role in the functioning of social, biological, economic, and technological systems. Despite widespread interest in detecting community structures in complex networks and exploring the effect of communities on collective dynamics, a deep understanding of the emergence and prevalence of communities in social networks is still lacking. Addressing this fundamental problem is of paramount importance in understanding, predicting, and controlling a variety of collective behaviors in society. An elusive question is how communities with common internal properties arise in social networks with great individual diversity. Here, we answer this question using the ultimatum game, which has been a paradigm for characterizing altruism and fairness. We experimentally show that stable local communities with different internal agreements emerge spontaneously and induce social diversity into networks, which is in sharp contrast to populations with random interactions. Diverse communities and social norms come from the interaction between responders with inherent heterogeneous demands and rational proposers via local connections, where the former eventually become the community leaders. This result indicates that networks are significant in the emergence and stabilization of communities and social diversity. Our experimental results also provide valuable information about strategies for developing network models and theories of evolutionary games and social dynamics.

communities | fairness | social diversity | networks | ultimatum game

Communities are ubiquitous in nature and society (1, 2). Nodes that share common properties often self-organize to form a community. Internet users with common interests, for example, establish online communities and frequently communicate (3). In human society, social communities with distinctive social norms form spontaneously (4). In protein–protein interaction networks, related proteins group together to execute specific functions within a cell (5).

How social communities emerge is one of the fundamental problems in social science. Game theory and models have offered powerful tools for exploring collective behaviors in animal and human society and our evolutionary origins (6–10). Recent theoretical studies found that network structure is significant in the emergence of mutually reinforcing communities among altruistic subjects in social games, such as the prisoner's dilemma (PD) game, the public goods game (PGG), and the ultimatum game (UG) (11–20). Although some experiments found that cooperation is stabilized in dynamical networks (21–24), stable communities have been rarely observed in laboratory experiments on a variety of static networks (25–32). As a result, how communities emerge in social network systems associated with evolutionary games continues to be an unanswered question.

Social game experiments demonstrate that there is inherent diversity among individuals in cultural and social attitudes toward cooperation, fairness, and punishment (33–37). However, communities with diverse individuals but common internal properties are ubiquitous in society, prompting us to wonder how diverse individuals are able to form communities. Our goal is to answer this question by experimentally exploring the emergence of communities in social networks associated with the UG. This game has been a paradigm for exploring fairness, altruism, and punishment behaviors that challenge the classical game theory assumption that people act in a fully rational and selfish manner (34–38). Thus, exploring social game dynamics allows us to offer a more natural and general interpretation of the self-organization of communities in social networks. In the UG, two players—a proposer and a responder—together decide how to divide a sum of money. The proposer makes an offer that the responder can either accept or reject. Rejection causes both players to get nothing. In a one-shot anonymous interaction if both players are rational and self-interested, the proposer will offer the minimum amount and the responder will accept it to close the deal. However, much experimental evidence has pointed to a different outcome: Responders tend to disregard maximizing their own gains and reject unfair offers (34–36, 38, 39). Although much effort has been devoted to explaining how fairness emerges and the conditions under which fairness becomes a factor (38, 40–46), a comprehensive understanding of the evolution of fairness in social networks via experiments is still lacking.

We conduct laboratory experiments on both homogeneous and heterogeneous networks and find that stable communities

Significance

Understanding how communities emerge is a fundamental problem in social and economic systems. Here, we experimentally explore the emergence of communities in social networks, using the ultimatum game as a paradigm for capturing individual interactions. We find the emergence of diverse communities in static networks is the result of the local interaction between responders with inherent heterogeneity and rational proposers in which the former act as community leaders. In contrast, communities do not arise in populations with random interactions, suggesting that a static structure stabilizes local communities and social diversity. Our experimental findings deepen our understanding of self-organized communities and of the establishment of social norms associated with game dynamics in social networks.

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SOCIAL SCIENCES

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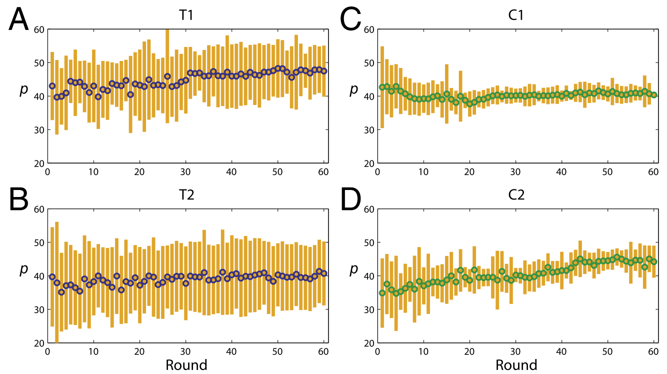

Fig. 1. Evolution of proposals in the treatment and control groups. (*A*–*D*) The proposers' offers *p* from round 1 to round 60 in the two treatment groups, T1 (*A*) and T2 (*B*), and the two control groups, C1 (*C*) and C2 (*D*), respectively. The mean value and the SD of *p* in each of the 60 rounds are denoted by circles and column bars, respectively. The average value of *p* in T1 is slightly higher than in the other groups, and the SD of *p* in T1 and T2 is much larger than that in C1 and C2. The results demonstrate that whether a structured network is regular or random has little effect on the average fairness of proposers, whereas the diversity in proposers, reflected by the SD, is remarkably promoted by network structure, in contrast to the two control groups with random interactions.

with different internal agreements emerge, which leads to social diversity in both types of networks. In contrast, in populations where interactions among players are randomly shuffled after each round, communities and social diversity do not emerge. To explain this phenomenon, we examine individual behaviors and find that proposers tend to be rational and use the (myopic) best-response strategy (43, 47), and responders tend to be irrational and punish unfair acts (34–36, 38, 39). Social norms are established in networks through the local interaction between irrational responders with inherent heterogeneous demands and rational proposers, where responders are the leaders followed by their neighboring proposers. Our work explains how diverse communities and social norms self-organize and provides evidence that network structure is essential to the emergence of communities. Our experiments also make possible the development of network models of altruism, fairness, and cooperation in networked populations.

Results

We conduct four groups of experiments with two treatment groups (T1 and T2) and two control groups (C1 and C2) (*Materials and Methods*). In T1 and T2 there is a static network structure among the players, a regular bipartite network for T1, and a random bipartite network for T2. In C1 and C2 the interactions among the players constantly change. Each subject plays a single unchanging role, either proposer or responder. We focus on the evolution of a proposer's offer p and a responder's minimum acceptance level q, which measures the degree of fair and unfair behaviors. Our main findings include (*i*) the diversity of p characterized by a much larger SD in T1 and T2 than in C1 and C2; (*ii*) the formation of local proposer communities in T1 and T2, seen in the spatiotemporal patterns of proposers; and (*iii*) the best-response strategy followed by proposers and the leader effect of irrational responders, i.e., they jointly establish social norms. Observation *iii* explains observations *i* and *ii*.

Diversity of Proposers. We first explore the evolution of p and q. Fig. 1 and *SI Appendix*, Fig. S1 show the mean values $\bar{p}$ and $\bar{q}$ of p and q and their SDs in each round for T1, T2, C1, and C2. We find that $\bar{p}$ in T1 is slightly higher than in the other groups. In T1, $\bar{p}$ slowly increases from approximately 40 to 45. In all of the other groups $\bar{p}$ is approximately 40 within 60 rounds. Similar phenomena are observed in $\bar{q}$; i.e., $\bar{q}$ of T1 is slightly higher than in the other groups and $\bar{q}$ of all groups is maintained at approximately 30. Table 1 shows the mean values $\bar{p}$ and $\bar{q}$ over 60 rounds. These findings in the experimental UG with limited neighbors are consistent with many one-pair experimental UGs in which on average $p = 40$ and $q = 30$ (34–36, 38, 39). These results indicate that network structure has little effect on the average behaviors of proposers and responders in a population.

On the other hand, the SD of p differs sharply between the treatment groups and the control groups. The SD of p in T1 and T2 is much larger than that in C1 and C2 (Fig. 1 and Table 1), indicating that network structures, whether regular or random, enable a strong proposer diversity that is lacking in populations with random interactions. In contrast, there are big SDs in q in both the treatment and control groups and there is little difference between them (details in Table 1 and *SI Appendix*, Fig. S1). In addition, both the mean value and the SD of q are constant in the experiments, which implies that the average behavior of responders changes little during the experiments. Although population structure plays a prominent role in the UG—reflected in the difference in the SD of p in the two classes—it does not affect the behavior of responders. Thus, we expect that network structure has a subtle effect on the UG and that this subtle effect will account for why proposer diversity emerges.

Emergence of Proposer Communities. To discover how network structure affects proposer diversity, we study the spatiotemporal patterns of the proposers. Surprisingly, Fig. 2 shows that in T1 and T2 proposers form local communities, which are shown in different colors (values of p). A community is a group of subjects with similar behavior and internal agreement. Proposer communities have similar values of p. After communities emerge, and especially in the final 10 rounds, their boundaries are clear and relatively invariant, indicating that they are approximately stable and rarely change. Each community is composed of adjacent proposers who make similar high or low offers and in Fig. 2 exhibit the same community color. Adjacent communities exhibit different colors, indicating that offers differ among communities. In C1 and C2, however, there are no clear communities and eventually a single homogeneous community of proposers with similar values of p (similar color) emerges. A snapshot in round 60 in T1 is shown in Fig. 3*A*. Four local communities are composed of adjacent proposers in the regular network (Fig. 3*A*). Analogous to T1, there are four local communities in the random network (Fig. 3*B*). Although in the random network there is no naturally occurring spatial order of nodes, we find a spatial order of nodes by using a simulated annealing algorithm to maximize the sum of shared neighbors between any two adjacent nodes (details in *SI Appendix, Supplementary Note 1*). The existence of local communities with different internal features accounts for the proposer diversity in structured populations.

Table 1. The mean value and SD of strategies in experiments

Group	Mean(*p*)	SD(*p*)	Mean(*q*)	SD(*q*)
T1	44.89	5.90	36.43	12.72
C1	40.27	1.64	31.66	7.61
T2	38.93	8.27	32.81	9.93
C2	40.74	2.25	31.53	7.87

Mean(*p*) and SD(*p*) represent the mean value and the SD of offers of all proposers, in which a proposer's offer is taken as the average of his/her offers *p* over 60 rounds, respectively. Similarly, mean(*q*) and SD(*q*) represent the mean value and the SD of minimum acceptance levels of all responders, respectively, in which a responder's minimum acceptance level is taken as the average of his/her minimum acceptance levels *q* over 60 rounds. T1, C1, T2, and C2 have the same meanings as those in Fig. 1.

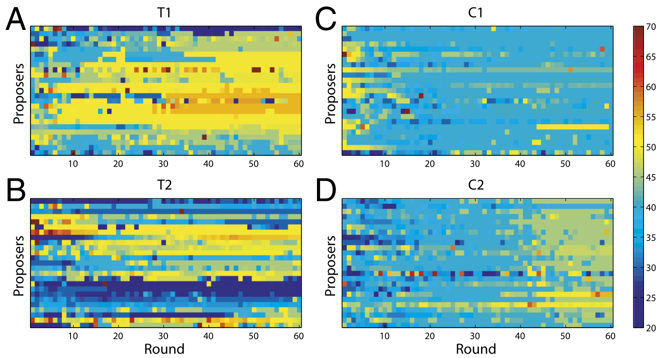

Fig. 2. Spatiotemporal patterns of proposers. (*A* and *B*) Spatiotemporal patterns of the proposers' offers *p* in the two treatment groups T1 and T2. (*C* and *D*) Spatiotemporal patterns of the proposers' offers *p* in the two control groups C1 and C2. The ordinate represents the spatial orders of proposers. Two proposers with most common neighbors will be adjacent to each other. The color bar represents the value of *p*. In *A* and *B*, neighboring proposers gradually form some local communities that can be distinguished by different colors (different values of *p*). The communities are stable as reflected by the presence of relatively clear and invariant boundaries among the communities after a number of rounds (e.g., 30 rounds in *A*). Each community is composed of some neighboring proposers who offer similar *p* as represented by a similar color. By contrast, in *C* and *D*, there are no local communities and a single homogeneous community of proposers with similar values of *p* as represented by a similar color arises. The local communities with different internal agreements in T1 and T2 account for the diversity in proposers. By contrast, in C1 and C2, the absence of local communities and the homogeneity of proposers account for the relatively small SD of proposals.

Note that although the formation of stable local communities has been predicted by a number of evolutionary game models, it has seldom been observed in experiments using both the UG and other social dilemma games, such as the PD and the PGG. Our work provides experimental evidence that local agreements in the form of communities are spontaneously achieved, which indicates that network structure plays a significant role in evolutionary games. It is worth noting that because the behavior of neighbors (i.e., values of p or q) in previous rounds returns in a descending order, the feedback information cannot be related to specific neighbors, precluding participants from using the reputations of their neighbors to make decisions (*SI Appendix*, Fig. S2). Thus, the network effect plays a deterministic role in the formation of proposer communities. Our findings provide evidence for network-induced communities and insight into the evolution of fairness and altruism in structured populations with limited social ties.

Behaviors of Proposers and Responders. To discover how diverse communities emerge, we explore the spatiotemporal diagram of responder behavior. Unlike the behavior of proposers, there is no obvious difference in the behavior of responders between the treatment and the control groups (*SI Appendix*, Fig. S3). There are no local responder communities, and adjacent responders exhibit inhomogeneity that increases the SD of q in all groups. The irrational behavior of responders reflected in the spatiotemporal diagram is consistent with the high SD of q (*SI Appendix*, Fig. S3). All of these results indicate that network structure has little influence on the decision-making process of responders. Unlike responders, most proposers are rational and make offers based on the (myopic) best-response strategy, as predicted by theoretical models (43, 47). Proposers tend to maximize their profits by using information about their neighbors' behaviors in the previous round. As the game progresses, over half of the proposers give a best response to their neighbors according to the definition of best response in the literature (43, 47) (details in *SI Appendix*, Fig. S4 and *Supplementary Note 2*).

Knowing how subjects make decisions is the key to understanding how proposer communities emerge. Proposer communities emerge from local interactions between the inherent diverse behaviors of responders (*SI Appendix*, Table S1) and the best-response behaviors of proposers. Within communities, proposers share a large fraction of neighbor responders. Because proposer behavior obeys the best-response strategy, they use their knowledge of the previous behavior of their common responders and offer similar amounts of money. These best-response behaviors induce the emergence of a local community. On the other hand, the inherent diverse behaviors of responders result in different communities with different internal agreements. In particular, when responders insist on high acceptance levels, they force their proposer neighbors to increase their offers, which leads to stable communities (Fig. 3*C*). Thus, local interactions are essential in the formation of local communities. This interpretation is supported by the absence of local communities in control groups with random interactions.

To examine whether some differences between the responders in the treatment group and those in the control groups may be responsible for the communities, we apply a shuffle technique in all of the experiments to test the effect of responder differences (28, 30). Specifically, we exchange the behavior sequences of the responders in the treatment groups with the behavior sequences of their counterparts in the control groups. This reshuffling does

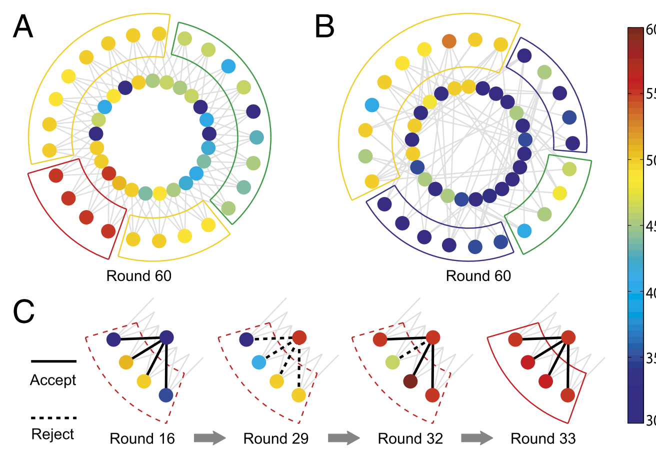

Fig. 3. Local communities of proposers. (*A* and *B*) A snapshot of the proposers' offers *p* and the responders' *q* in round 60 for (*A*) T1 with a regular network and for (*B*) T2 with a random network. The subjects are arranged in two rings, where the outside ring represents proposers and the inside ring represents responders. The color bar represents the value of *p* and *q*. Communities are highlighted by colored boxes. The arrangement of proposers is the same as in Fig. 2 (two subjects with most common neighbors are adjacent to each other) but with periodic boundary conditions. The regular network offers a natural sequential order but there is no such order for the random network. We assign the spatial order of the nodes in random networks by using a simulated annealing algorithm. The order is exclusively based on the topology rather than the acts of subjects. (*C*) The evolution of a fairly stable community in T1. The snapshots of the community in four rounds are shown. The responder can be regarded as a "leader" of this community and is followed by the four neighboring proposers. In round 16, the responder's minimum acceptance level *q* was relatively low and all neighboring proposal *p*s were accepted. In round 29, the responder's *q* was increased and all neighboring *p*s were rejected. Because the proposers are relatively rational, they gradually increased their *p*s to make deals with the responder. In round 32, three proposers made deals by enhancing their *p*s, and a proposer's *p* is higher than the responder's *q*. In round 33, all of the proposers made deals with the responder and their *p*s were equal to or slightly higher than the responder's *q*.

not change a player's dependence on his or her own previous actions because the order of the actions over 60 rounds is not altered. We then calculate the best-response offers in each group and find that the SD of p in the shuffle games with network structures is still higher than that in the shuffle games with random interactions, suggesting that the differences between the responders in the treatment and control groups do not account for the emergence of the communities (*SI Appendix*, Table S2). Thus, local interactions play an essential role in the emergence and maintenance of local communities.

Simulations on Complex Networks. Recent interest in evolutionary games in scale-free networks prompts us to explore the UG on scale-free networks (11–13, 15, 18, 20, 30). In general, a scale-free network must be of a certain size to exhibit its typical structural feature, that is, the presence of hubs with a large number of neighbors (48). However, an experimental UG on a large network is limited by our ability to conduct large-scale experiments. To overcome this, we simulate the UG on scale-free networks. Specifically, because proposers use the best-response strategy in treatment and control groups, we assume that proposers in scale-free networks exhibit a similar behavior (31). In contrast, it is difficult to use simple mechanisms to capture the irrational behavior of responders. This problem can be solved by focusing on responder behavior in the experiments and discovering that behaviors are quite similar in the different experiments. We build a database of all responder behavior sequences obtained in the four experiments, randomly pick sequences from the database, and assign them to responders in the scale-free network. Table 2 shows that for different network sizes and average degrees, the SD of p in scale-free networks is always much higher than that in populations with random interactions, but that there is no obvious difference in the mean value of p. The spatiotemporal pattern of proposers in scale-free networks also exhibits the formation of local communities (*SI Appendix*, Fig. S5). These results agree with our experimental findings in regular and random networks.

To test whether our findings depend on the specific ratio between proposers and responders, we carry out additional simulations for networks with different proposer–responder ratios. Two types of bipartite networks are considered. In the first type all proposers and responders have the same degrees, respectively, and in the second type the degrees of proposers and responders can differ. Similar to the simulations in scale-free networks, we randomly choose responder behaviors from the database that includes all responder behavior sequences and assume that proposers follow the best-response strategy. As shown in *SI Appendix*, Table S3, for four different proposer–responder ratios, the SD of p in structured populations is much higher than in populations with random interactions. Thus, our results are robust against changes in the ratio between proposers and responders.

Table 2. The mean value and SD of proposers' offers in scale-free networks

N	$\langle k \rangle$	Structured/unstructured Mean(p)	Structured/unstructured SD(p)
100	4	41.30/41.30	5.36/2.14
	6	42.81/42.89	4.26/1.54
	8	43.60/43.52	3.46/1.17
500	4	41.10/41.11	5.71/2.16
	6	42.73/42.71	4.58/1.55
	8	43.60/43.58	3.81/1.18
1,000	4	40.95/40.92	5.78/2.17
	6	42.69/42.70	4.66/1.54
	8	43.61/43.60	3.89/1.19

N represents the network size and $\langle k \rangle$ represents the average nodal degree. Structured and unstructured correspond to virtual experiments with static scale-free networks and constantly changing networks with the same node degrees as their counterparts with fixed structures. Other notations have the same meaning as that in Table 1. The results are calculated by using from round 2 to round 60 and implementing 1,000 independent realizations.

Discussion

Our experimental results, shuffle tests, and simulations demonstrate that stable communities with different internal agreements emerge in both regular and complex networks governed by the UG. Thus, the social diversity among proposers emerges and persists. In contrast, in populations with random interactions the proposers remain homogeneous and no communities are established. The diverse communities emerge from the local interactions between irrational responders with inherent heterogeneous demands and rational proposers. In general, proposers with common neighbor responders who act as leaders constitute a community with internal agreement. The different findings between the treatment and control groups indicate that networks are significant in the emergence of social norms, communities, and social diversity. Thus, our work explains how communities with common internal properties and social norms can emerge in a social network in which individuals are diverse. Note that our findings also suggest that even when all proposers have the same intelligent strategy (i.e., best response) and all subjects in the social network have equal status, diverse communities can arise. This result may explain why different social norms can be established even in homogeneous environments (4, 49, 50).

Our results also indicate that local interactions in network structures are only a necessary and not a sufficient condition for the formation of local communities. The self-organization of communities also requires an inherent diversity among individuals. In our UG experiments, local agreements are achieved because a majority of proposers are rational. Some of the irrational responders who insist on high acceptance levels become "leaders" who are followed by their neighboring proposers. This leader effect has been observed in other evolutionary games. For example, previous studies report that cooperating leaders play an important role in increasing a group's average contribution in PGGs (51, 52). However, how the cooperative communities are established in social dilemma games in social networks remains an open question.

Our work also raises other questions about the emergence of communities and their effects on evolutionary dynamics. First, how does inherent diversity among individuals arise? One possible answer is provided in a recently proposed model by Bear and Rand (53) in which intuitive rejection and deliberative acceptance have evolutionary advantages (53). Thus, heterogeneity at an individual level in our experiments might stem from different deliberation costs in which responders with a higher deliberation cost tend to make decisions based on intuition. Thus, they may have higher acceptance level q for closing a deal with their neighboring proposers. Second, how does cultural difference affect the experimental findings of communities and social diversity? Although additional experiments are needed to fully address this question, previous experiments provide hints that anticipate the effect of cultural difference. Specifically, there is no significant difference between responder behavior in our experiments and that in previous experiments of UG conducted in different countries (34). Thus, qualitatively similar results may be obtained if the experiments are conducted in other countries. Third, most theoretical models for networked UG assume that a subject can act as both a proposer and a responder (18–20). Thus we may ask how the two identities of subjects influence each other and affect the formation of local communities predicted by theoretical models. Taken together, further effort is needed to offer a better understanding of the emergence of communities in social networks.

Materials and Methods

This research was approved by School of Systems Science, Beijing Normal University on the use of human subjects, and informed consent was obtained from subjects before participation. We recruit 50 participants in each of four groups. Half of them are randomly assigned proposers and half are randomly assigned responders, and assigned player roles do not change during the experiment. Each participant in the treatment groups is assigned a location within a static network and designated either a proposer or a responder. In the treatment groups the UG is structured and participants must play the UG with their immediate neighbors (two subjects are neighbors if they are directly connected). All of the proposers' neighbors are responders and vice versa. To be consistent with theoretical models, in each round all subjects must use one decision behavior as they interact with their neighbors; that is, a proposer must make the same offer p ($0 \leq p \leq 100$) to all of his or her neighboring responders, and a responder must indicate the same minimum acceptance level q ($0 \leq q \leq 100$) to all of his or her neighboring proposers (18–20). For T1 we construct a regular bipartite network in which each node has four neighbors. For T2 we build a random bipartite network in which the number of neighbors ranges from two to six (with an average degree of four).

We compare the results from the treatment groups with the results from the two control groups (populations with random interactions), C1 and C2, to explore the network effect on fairness and altruism. Specifically, to make an unbiased comparison between the treatment and control groups, in C1 and C2 we use a randomly rewired bipartite network with the same node degrees as in the treatment groups. In the rewired network the neighbors of each node are chosen randomly from the other type of nodes in each round, but the number of each node's neighbors is unchanged.

Each group of experiments includes 60–70 rounds. To prevent any final-round effect, we do not tell the participants the number of rounds they will play. In each round, information gathered in the previous round is given to each player, including the player's own behavior and payoff and the behavior of the player's neighbors. The payoff of a player in each round is the sum of the benefits gained from interacting with all of the neighbors of the player normalized by the number of neighbors. To simplify their decision-making processes, we rank neighbor behaviors in a descending order such that players can easily evaluate their behaviors (*SI Appendix*, Fig. S2). For a further explanation of the experimental design, see *SI Appendix, Supplementary Notes 3–5*.

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Supplementary Information for

Emergence of Communities and Diversity in Social Networks

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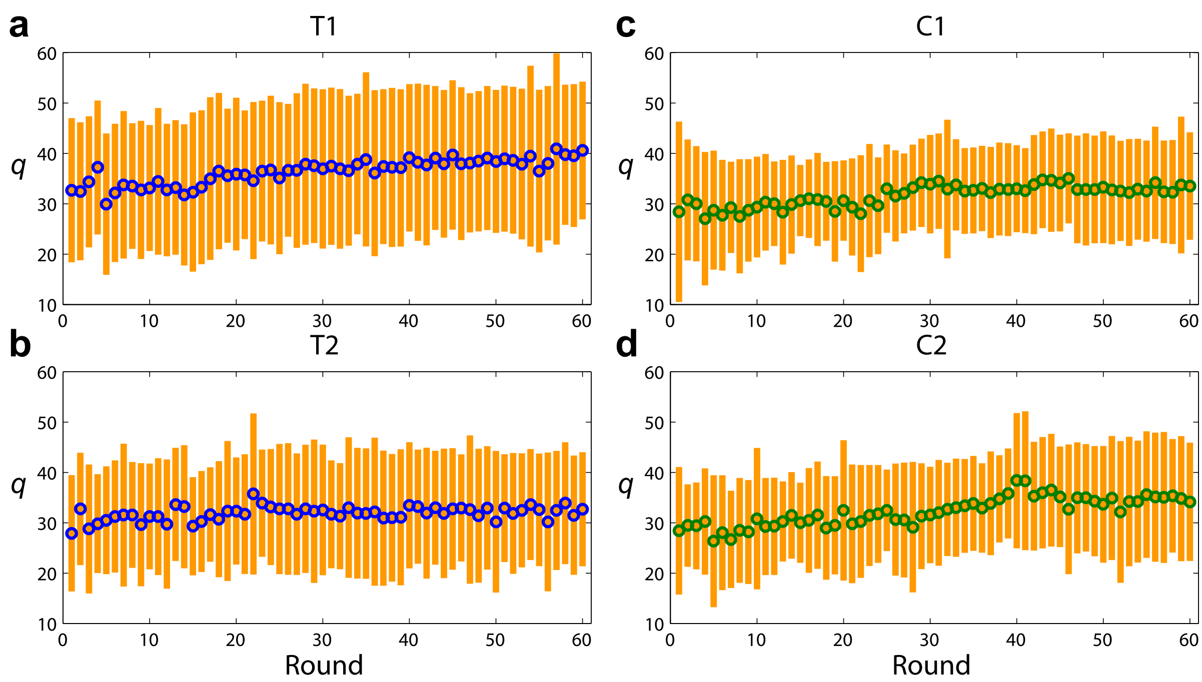
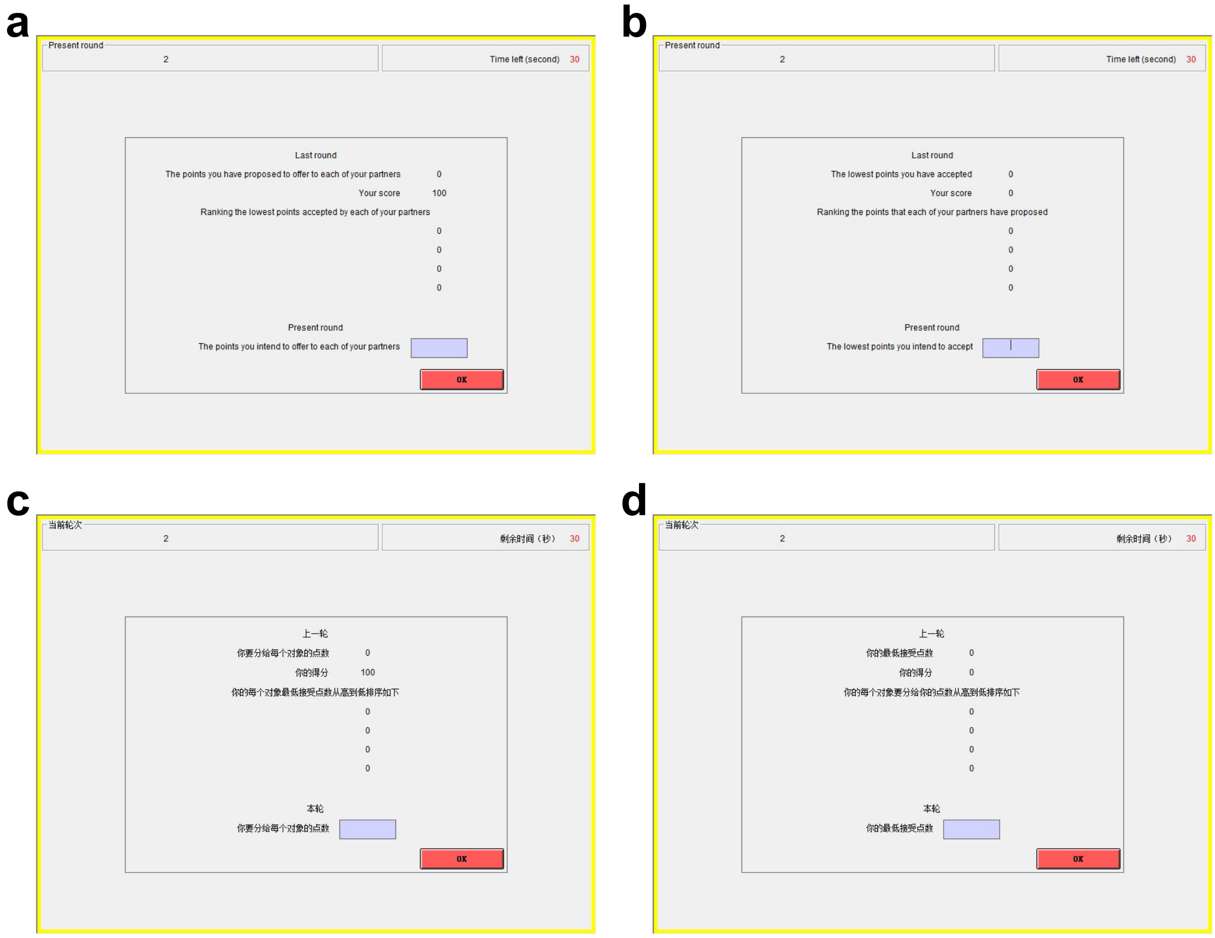
Contents

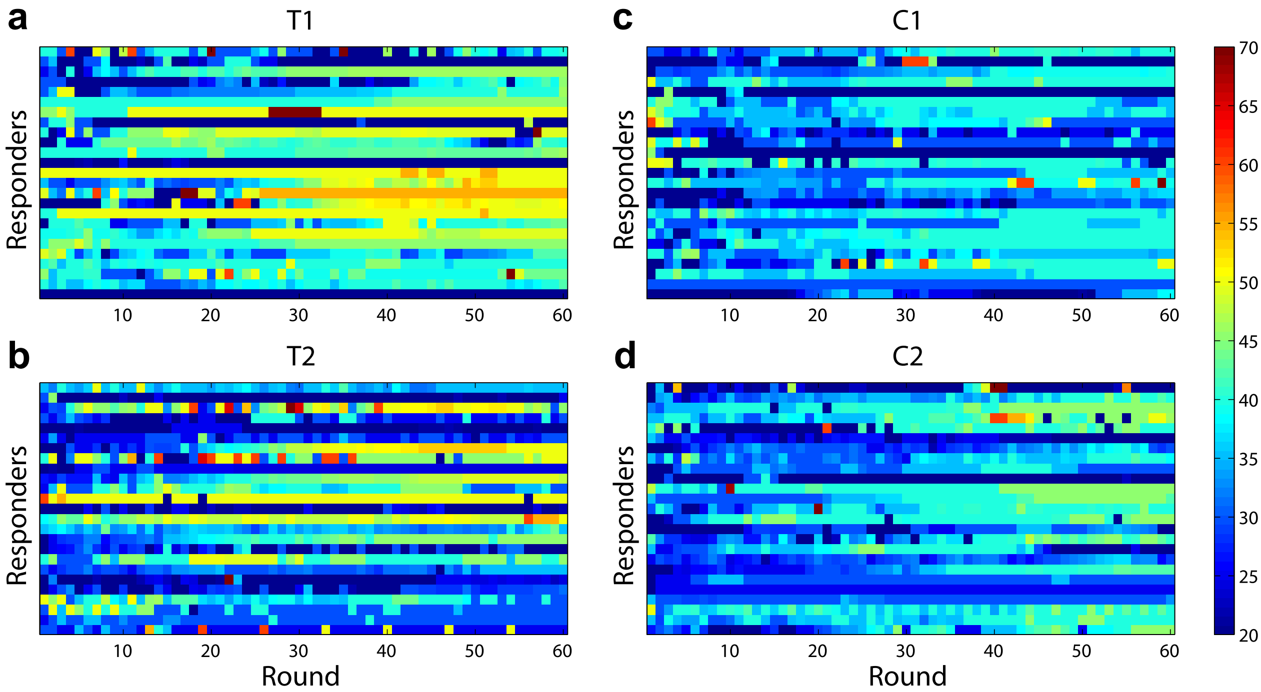
1 Supplementary Figures



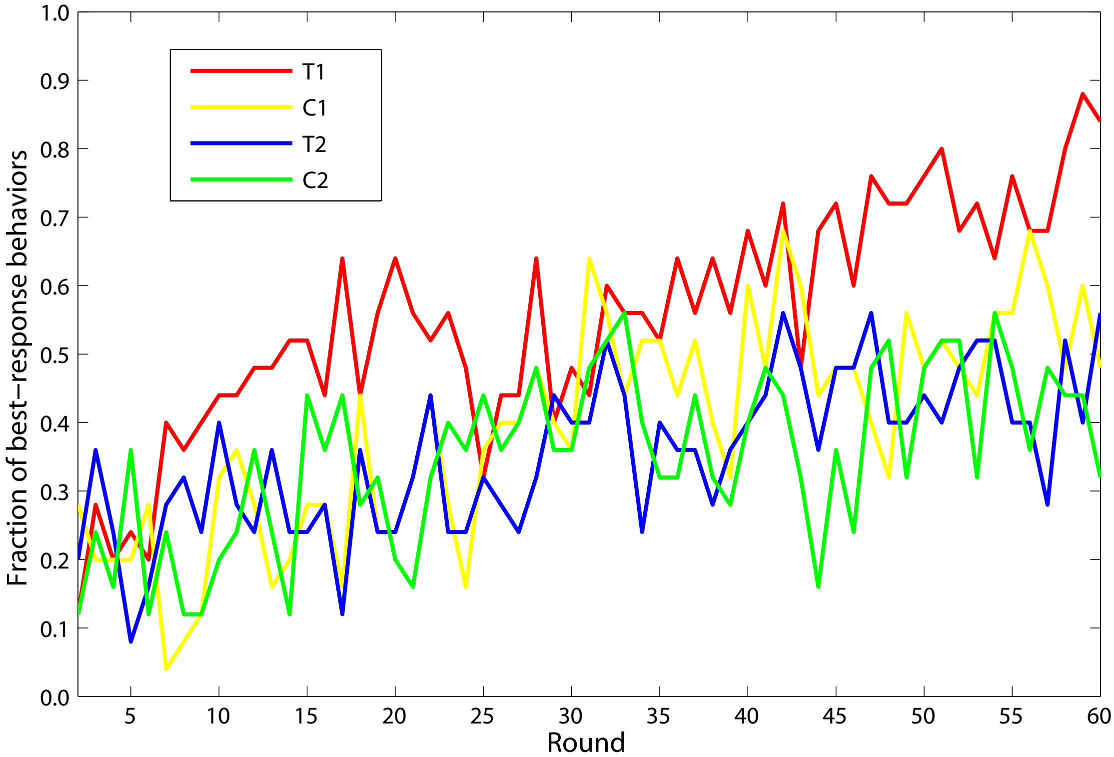
Supplementary Figure S1: Evolution of the minimum acceptance level q in the treatment and control groups. (**a**-**d**) The evolution of q in the two treatment groups, T1 (**a**) and T2 (**b**), and the two control groups, C1 (**c**) and C2 (**d**), respectively. The mean value and the standard deviation (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.



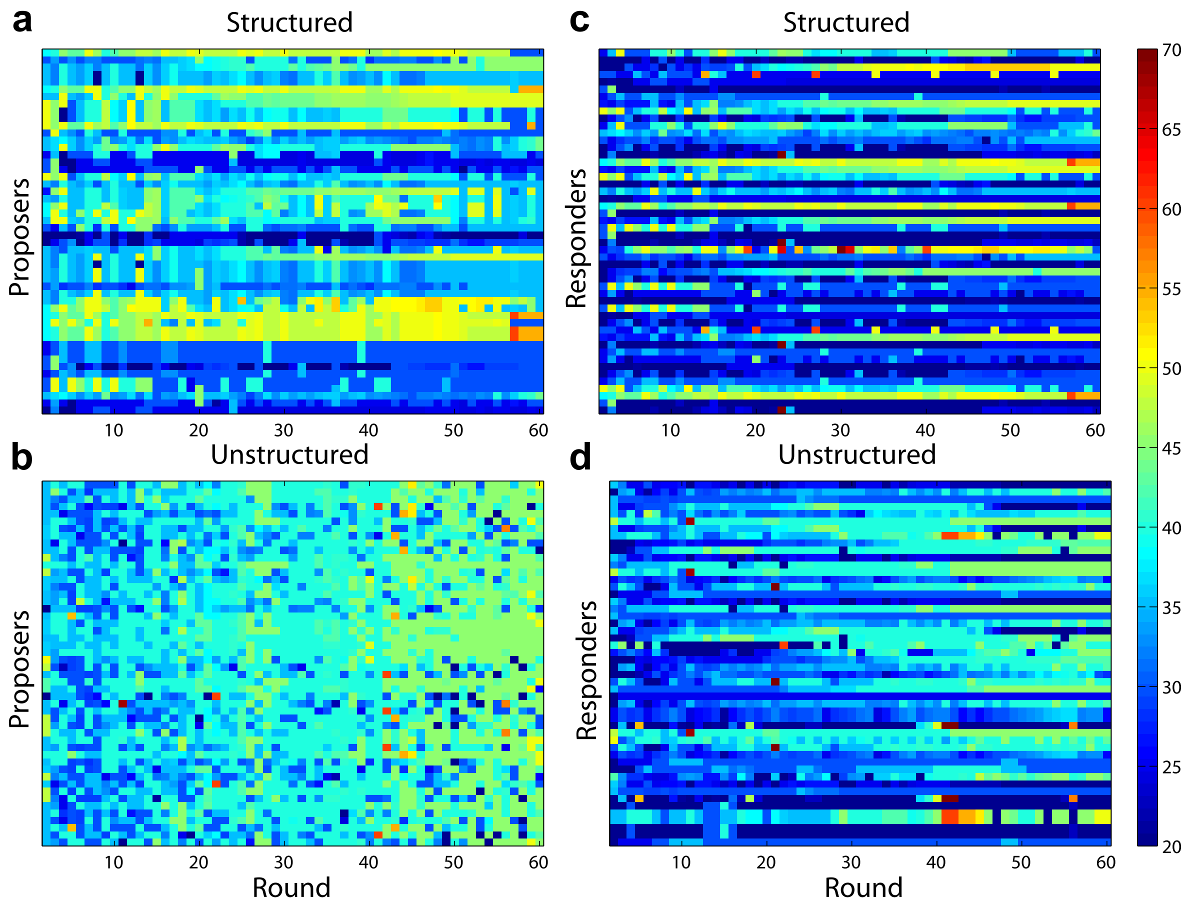
Supplementary Figure S2: Screen shots of experimental interfaces. (**a**,**b**) Interface of proposers (**a**) and responders (**b**) in English. (**c**,**d**) Interface of proposers (**c**) and responders (**d**) in Chinese. We used the two interfaces in Chinese in the experiments and the English versions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

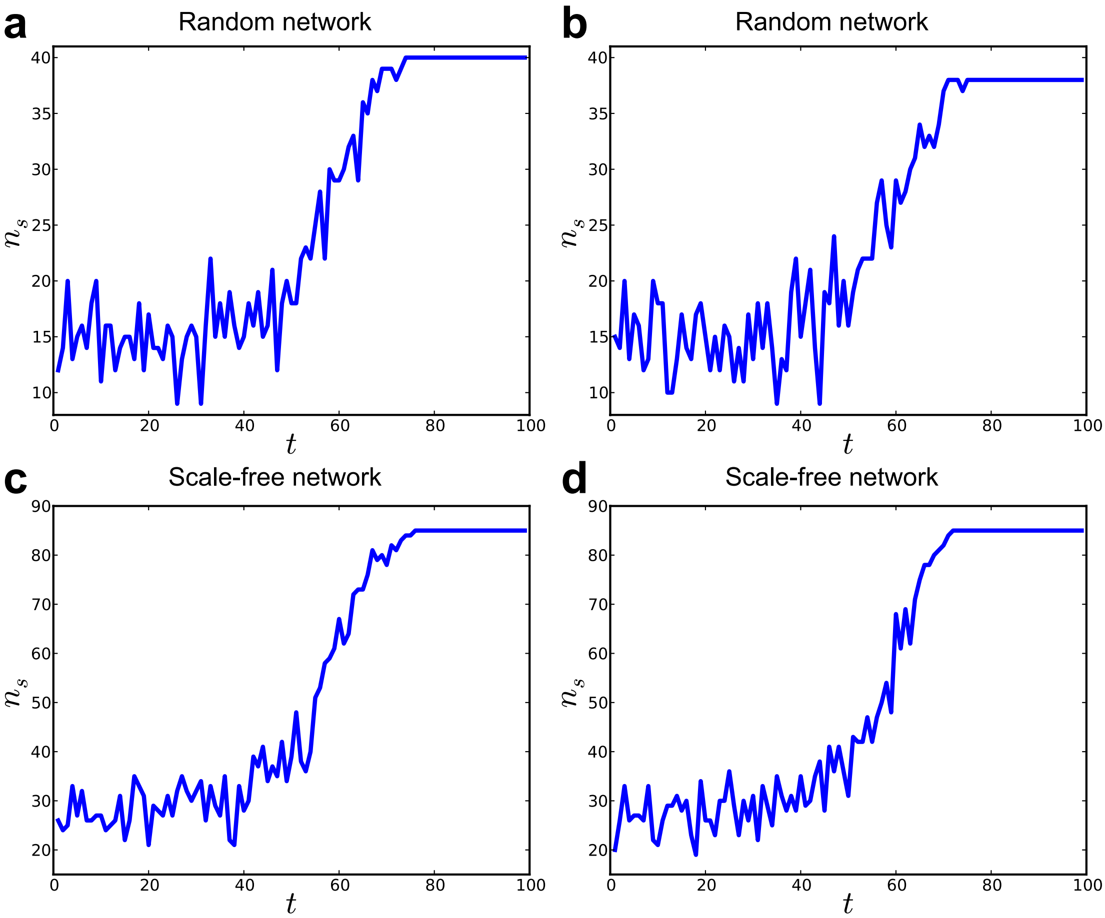


Supplementary Figure S4: The fraction of rational proposers with best-response strategy. The frequencies of best-response strategy from round 2 to round 60 in T1 (red), C1 (yellow), T2 (blue) and C2 (green). In round 2, there are only 18 rational proposers in the 100 proposers (3 in T1, 7 in C1, 5 in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

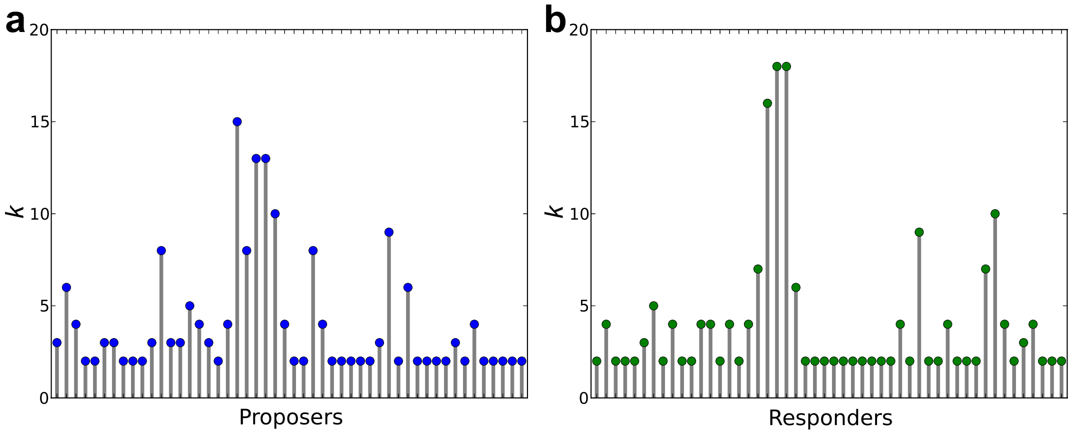


Supplementary Figure S5: Spatio-temporal patterns of proposers and responders in scale-free networks. (**a**) Spatio-temporal patterns of the proposers' offers p in structured scale-free bipartite network and clear local clusters are observed. (**b**) Spatio-temporal patterns of the proposers' offers 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 network	46.36	4.75
T1 without network	39.26	0.58
C2 on T2 network	40.11	7.64
T2 without 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. Mean(p) and 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.

				mean(p)		std(p)	
N_P	N_R	$\langle k \rangle_P$	$\langle k \rangle_R$	Regular	Random	Regular	Random
				(Structured / unstructured)		(Structured / unstructured)	
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 $n_{\rm s}$ in terms of the number of common neighbors of all pairs of immediately adjacent nodes, $n_{\rm s} \equiv \sum_{i=1}^{N/2-1} n_{i,i+1} + n_{N/2,1}$ (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 $q_1, ..., q_k$ (with $q_1 < \cdots < q_k$), the best strategy was $p = \mathrm{argmax}_{q_i}\{i \times (100 - q_i)/k\}$, 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, avoids subject confusion, and reduces 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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