Static network structure can stabilize human cooperation

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Edited by Jose A. Scheinkman, Columbia University, New York, NY, and approved October 30, 2014 (received for review January 9, 2014)

The evolution of cooperation in network-structured populations has been a major focus of theoretical work in recent years. When players are embedded in fixed networks, cooperators are more likely to interact with, and benefit from, other cooperators. In theory, this clustering can foster cooperation on fixed networks under certain circumstances. Laboratory experiments with humans, however, have thus far found no evidence that fixed network structure actually promotes cooperation. Here, we provide such evidence and help to explain why others failed to find it. First, we show that static networks can lead to a stable high level of cooperation, outperforming well-mixed populations. We then systematically vary the benefit that cooperating provides to one's neighbors relative to the cost required to cooperate (b/c), as well as the average number of neighbors in the network (k). When $b/c > k$, we observe high and stable levels of cooperation. Conversely, when $b/c \leq k$ or players are randomly shuffled, cooperation decays. Our results are consistent with a quantitative evolutionary game theoretic prediction for when cooperation should succeed on networks and, for the first time to our knowledge, provide an experimental demonstration of the power of static network structure for stabilizing human cooperation.

Prisoner's Dilemma | evolutionary game theory | economic games | structured populations | assortment

Human societies, in both ancient and modernized circumstances, are characterized by complex networks of cooperative relationships (1–10). These cooperative interactions, where individuals incur costs to benefit others, increase the greater good but are undercut by self-interest. How, then, did the selfish process of natural selection give rise to cooperation, and how might social arrangements or institutions foster cooperative behavior? Evolutionary game theory has offered various explanations, in the form of mechanisms for the evolution of cooperation (10). For example, theory predicts (and experiments confirm) that repeated interactions between individuals and within groups can promote cooperation (11–22), as can competition between groups (23–26).

However, one important class of theoretical explanations remains without direct experimental support: the prediction that static (i.e., fixed) network structure should have an important effect on cooperation (27–40). When interactions are structured, such that people only interact with their network "neighbors" rather than the whole population, the emergence of clustering (or "assortment") is facilitated. Clustering means that cooperators are more likely to interact with other cooperators, and therefore to preferentially receive the benefits of others' cooperation. Thus, clustering increases the payoffs of cooperators relative to defectors and helps to stabilize cooperation. Across a wide array of model details and assumptions, theoretical work has shown that static networks can promote cooperation, making spatial structure one of the most studied mechanisms in the theory of the evolution of cooperation in recent years (27–40).

However, numerous laboratory experiments have found that static networks do not increase human cooperation relative to random mixing (41–50) [in contrast to dynamic networks, where players can make and break ties, which have been shown to promote cooperation experimentally (42, 46, 51)]. One explanation for these findings is that static networks cannot maintain assortment because humans often spontaneously switch strategies (41). This conclusion is a pessimistic one for the large body of theoretical work demonstrating the success of cooperation on such networks.

Here, we propose an alternative explanation. A central theoretical result is that networks do not promote cooperation in general. Rather, specific conditions must be met before cooperation is predicted to succeed. Thus, prior experiments may have failed to find a positive effect of static networks on cooperative behavior because they involved particular combinations of payoffs and network structures that were, in fact, not conducive to cooperation.

To assess this possibility, we conduct a set of laboratory experiments using artificial social networks. We arrange subjects on a ring connected to $k/2$ neighbors on each side (resulting in k total neighbors in the network; Fig. 1) and have them play a series of Prisoner's Dilemma games. In each game, they can defect (D) by doing nothing or cooperate (C) by paying a cost of $c = 10k$ units to give each of the k neighbors a benefit of b units (they must choose a single action, C or D, rather than choosing different actions toward each neighbor). Following each decision, subjects are informed of the decisions of each of their neighbors, as well as the total payoff they and each neighbor earned for the round.

Significance

Human populations are both extremely cooperative and highly structured. Mathematical models have shown that fixed network interaction structures can lead to cooperation under certain conditions, by allowing cooperators to cluster together. Here, we provide empirical evidence of this phenomenon. We explore how different fixed social network structures can promote cooperation using economic game experiments. We find that people cooperate at high stable levels, as long as the benefits created by cooperation are larger than the number of neighbors in the network. This empirical result is consistent with a rule predicted by mathematical models of evolution. Our findings show the important role social networks can play in human cooperation and provide guidance for promoting cooperative behavior.

Author contributions: D.G.R., M.A.N., J.H.F., and N.A.C. designed research, performed research, analyzed data, and wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

Freely available online through the PNAS open access option.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1400406111/-/DCSupplemental.

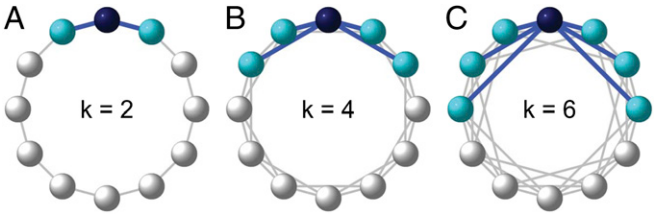

Fig. 1. Examples of the network structure for the $k = 2$ (*A*), $k = 4$ (*B*), and $k = 6$ (*C*) cases. Consider the topmost player as the ego (in dark blue); her links are highlighted in blue, and her neighbors are colored light blue.

Our experiments take inspiration from recent work in evolutionary game theory predicting that in static networks, cooperation will be favored over time if and only if the condition $b/c > k$ is satisfied (33, 37); discussion of the derivation of this condition, which arises from a model where players use fixed strategies (C or D) and then learn by imitating successful neighbors, is provided in *SI Appendix*. We therefore experimentally test (*i*) whether stable cooperation emerges in networks satisfying the $b/c > k$ condition and (*ii*) whether, as a result, networked interactions promote cooperation relative to well-mixed populations when $b/c > k$.

Results

In experiment 1, we fix $b/c = 6$ and $k = 2$, and recruit $n = 109$ students from Yale University to play 50 rounds of our game (8.4 subjects per session on average). Subjects are assigned either to a "network" treatment, in which their position on the ring is held constant every round, or a "well-mixed" treatment, in which their position is randomly shuffled every round (subjects in the well-mixed treatment are informed of this shuffling). Further details are provided in *Methods*.

Because the $b/c > k$ condition is satisfied, we expect cooperation to succeed in the network treatment. As shown in Fig. 2, our results are consistent with this theoretical prediction. We observe a high stable level of cooperation when subjects are embedded in the network (no significant relationship between cooperation and round number; $P = 0.290$). In the well-mixed treatment, by contrast, cooperation decreases over time (relationship between cooperation and round is significantly more negative in the well-mixed treatment compared with the network treatment; $P = 0.030$). As a result, cooperation rates in the second half of the session are significantly higher in the network treatment than in the well-mixed treatment [$P = 0.039$; similar results are obtained when considering the last third ($P = 0.027$) or quarter ($P = 0.033$) of the session; P values generated using logistic regression at the level of the individual decision with robust SEs clustered on subject and session, including a control for the total number of players in the session]. Statistical details are provided in *SI Appendix*.

Thus, experiment 1 demonstrates that interaction structure does matter for stabilizing human cooperation and that static networks can promote cooperation under the right conditions.

In experiment 2, we build on this finding by providing evidence that it is the theoretically motivated $b/c > k$ condition in particular that determines when cooperation succeeds on networks. To do so, we take advantage of the online labor market Amazon Mechanical Turk (AMT) (52) to recruit a large number of subjects (1,163 in total) and systematically vary b/c and k across the values of 2, 4, and 6 in our network treatment. Thus, we have nine main treatments: [$k = 2$, $k = 4$, $k = 6$] × [$b/c = 2$, $b/c = 4$, $b/c = 6$]. We also include three additional well-mixed control conditions: one for each [b/c,k] combination that satisfies the $b/c > k$ criterion. We run four experimental sessions of each treatment, with each consisting of 24.2 subjects on average (no subject participated in more than one session). Given the practical constraints of online experiments, games in experiment 2 last 15 rounds rather than 50 rounds as in experiment 1. Because of this shorter length, subjects are not told the total number of rounds to avoid substantive end-game effects.

We begin by considering the network treatments and ask whether the $b/c > k$ condition determines the success of cooperation. Consistent with the results for experiment 1 and theoretical predictions, we observe a stable high level of cooperation when $b/c > k$ (Fig. 3*A*). After an initial transient adjustment, cooperation in the $b/c > k$ treatments stabilizes in the second half of the game (no significant relationship between cooperation and round number; $P = 0.838$), whereas cooperation continues to decline in the $b/c \leq k$ treatments [$P = 0.028$; results are equivalent when considering the last third of the game instead of the second half or when defining the second half as starting at round 8 instead of round 9 (*SI Appendix*)]. This difference in how cooperation unfolds over time is further demonstrated by a significant interaction between round number and a $b/c > k$ indicator ($P = 0.001$) in a regression with all of the data.

As a result, in the final round, cooperation is significantly higher when $b/c > k$ compared with $b/c \leq k$ (Fig. 3*B*; $P = 0.002$). Importantly, there is no significant difference in final round cooperation comparing $b/c < k$ with $b/c = k$ ($P = 0.355$) and there is more final round cooperation in $b/c > k$ compared with $b/c = k$ ($P = 0.034$). Thus, we provide evidence that $b/c > k$, in particular, is needed for stable networked cooperation (P values generated using logistic regression at the level of the individual decision with robust SEs clustered on subject and session, including a control for the total number of players in the session; statistical details are provided in *SI Appendix*).

These differences in the level of cooperation reflect deeper differences in how players are distributed over the network. When $b/c > k$, clusters of cooperators emerge and are maintained, whereas no such clusters form when $b/c \leq k$. We quantify clustering following the standard definition of assortment in evolutionary game theory (53), operationalized here as a cooperator's average fraction of cooperative neighbors minus a defector's average fraction of cooperative neighbors. As shown in Fig. 4*A*, assortment rapidly emerges when $b/c > k$, but not when $b/c \leq k$. Thus, we observe a level of assortment that is significantly greater than zero for $b/c > k$ ($P < 0.001$), but not for $b/c \leq k$ ($P = 0.461$), and we observe significantly more assortment at $b/c > k$ than $b/c \leq k$ ($P < 0.001$). In other words, the $b/c > k$ environment gives rise to substantial clustering of cooperators, stabilizing cooperation. To illustrate this point, sample $b/c > k$ and $b/c \leq k$ networks for rounds 1 through 5 are shown in Fig. 4 *B* and *C*. Despite similar initial levels of cooperation across the two networks, the

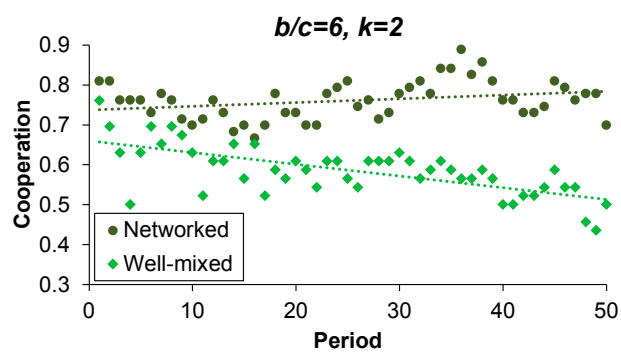

Fig. 2. Networked interactions promote cooperation when $b/c = 6$ and $k = 2$ in experiment 1, run in the physical laboratory. Shown is the fraction of subjects choosing cooperation in each round, for network (dark green circles) and well-mixed (light green diamonds) conditions.

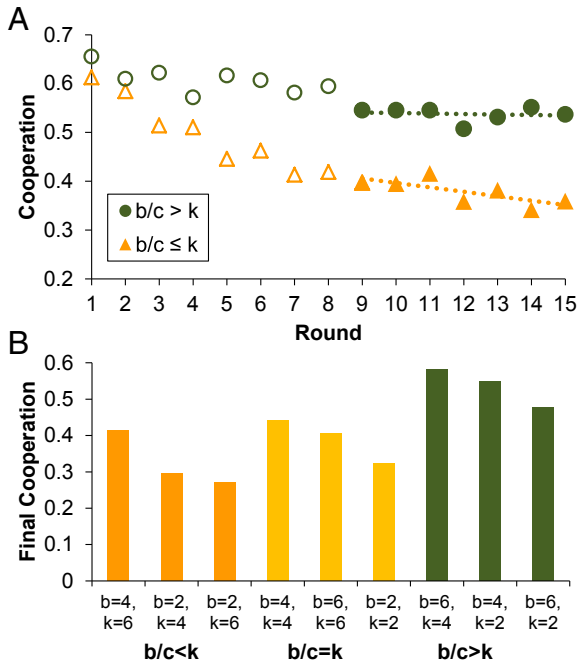

Fig. 3. Stable cooperation emerges when $b/c > k$, but not $b/c \leq k$, in experiment 2, run online. (*A*) Fraction of subjects choosing cooperation in each round, for $b/c > k$ (green circles) and $b/c \leq k$ (orange triangles). Observations from the first half of the game are open, and observations from the second half are filled. (*B*) Fraction of subjects choosing cooperation in the final round, for each [b/c,k] combination. Bars are grouped by [$b/c < k$, $b/c = k$, $b/c > k$] and are sorted in decreasing order of final cooperation level within each grouping.

distribution of cooperators within the networks quickly becomes noticeably different [P values generated using linear regression taking one observation per session per round, with robust SEs clustered on session; results are robust to controlling for k (*SI Appendix*)].

This assortment has important strategic implications. Defectors earn significantly higher payoffs than cooperators when $b/c \leq k$ ($P < 0.001$; Fig. 5*A*). The clustering that arises when $b/c > k$, however, allows cooperators to interact preferentially with other cooperators. Thus, the cost of cooperating may be balanced out by increased access to the benefits created by other cooperators, improving the payoffs of cooperators relative to defectors. Indeed, cooperators earn significantly higher payoffs relative to defectors when $b/c > k$ compared with $b/c \leq k$ ($P < 0.001$), so much so that when $b/c > k$, defectors no longer earn significantly more than cooperators ($P = 0.152$; Fig. 5*B*; P values generated using linear regression on payoff relative to session average per subject per round, with robust SEs clustered on subject and session; statistical details are provided in *SI Appendix*).

Thus far in experiment 2, we have shown that stable cooperation emerges in static networks when $b/c > k$ and that this cooperation is supported by assortment. We now provide evidence that it is indeed the network structure of interactions that is driving these results, by ruling out two potential alternatives.

First, we show that the key factor determining outcomes is the $b/c > k$ criterion, rather than merely the b/c ratio itself (which is larger when $b/c > k$ than when $b/c \leq k$). When we include a control for the b/c ratio (statistical details are provided in *SI Appendix*), we continue to find a significant interaction between round number and a $b/c > k$ indicator ($P = 0.004$). We also continue to find that when comparing $b/c > k$ to $b/c \leq k$, there is significantly more cooperation in the final round ($P = 0.047$), significantly more assortment ($P < 0.001$), and significantly higher payoffs of cooperators compared with defectors ($P < 0.001$). Thus, the network properties (i.e., the relationship between b/c and k) must be considered, and the results cannot be explained by b/c alone.

Second, we replicate the result from experiment 1 that shuffling the network results in a decay of cooperation even if the $b/c > k$ condition is satisfied. In our well-mixed $b/c > k$ control conditions, there is (by design) significantly less assortment than in the networked treatments ($P = 0.001$). As a result, we find that cooperation significantly declines in the second half of the game when the population is well mixed ($P = 0.004$), even though $b/c > k$. Furthermore, the well-mixed controls show less cooperation in the final round ($P = 0.033$) and lower payoffs to cooperators compared with defectors ($P < 0.001$). Together with experiment 1, these results show that it is not enough to interact with k players in each round. Interactions must be embedded in static networks to achieve stable cooperation in our experiments (statistical details and further analysis are provided in *SI Appendix*).

Discussion

Here, we have demonstrated the power of static interaction networks to promote human cooperation. With the right combination of payoffs and structure, networked interactions allow stable cooperation via the clustering of cooperators. This clustering offsets the costs of cooperating and makes it possible to maintain high levels of cooperation in sizable groups and to avoid the tragedy of the commons. Our experimental results support the substantial theoretical literature suggesting that cooperation can be favored in structured populations under the right conditions (27–40). Our findings provide insight into the

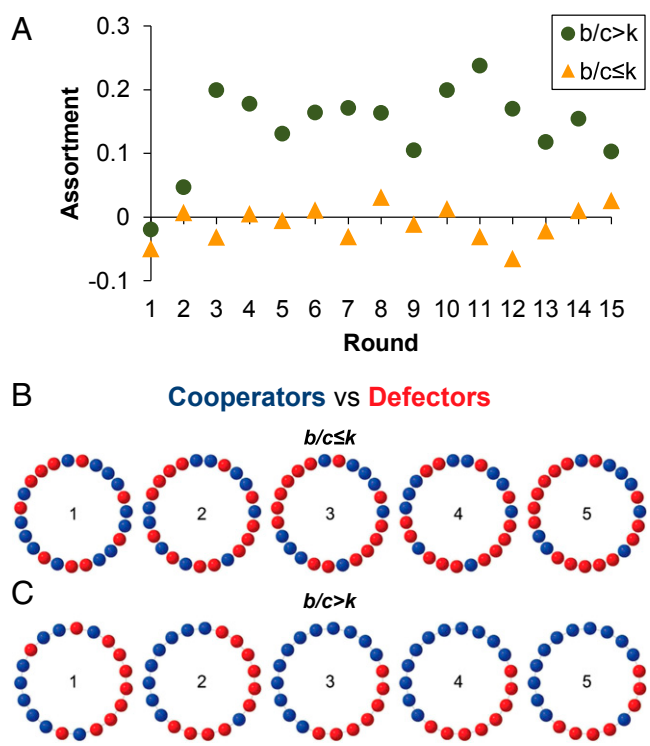

Fig. 4. Substantial assortment emerges when $b/c > k$, but not $b/c \leq k$. (*A*) Shown is the average level of assortment (cooperators' average number of cooperative neighbors minus defectors' average number of cooperative neighbors) by round for $b/c > k$ (green circles) and $b/c \leq k$ (yellow triangles). Also shown are two sample networks across the first five rounds (which are labeled), where cooperators are shown in blue and defectors in red; low clustering with $b/c \leq k$ (*B*; $b/c = 2$, $k = 2$) and high clustering with $b/c > k$ (*C*; $b/c = 6$, $k = 2$). Despite similar initial levels of cooperation, clustering maintains cooperation when $b/c > k$, whereas cooperation decays when $b/c \leq k$.

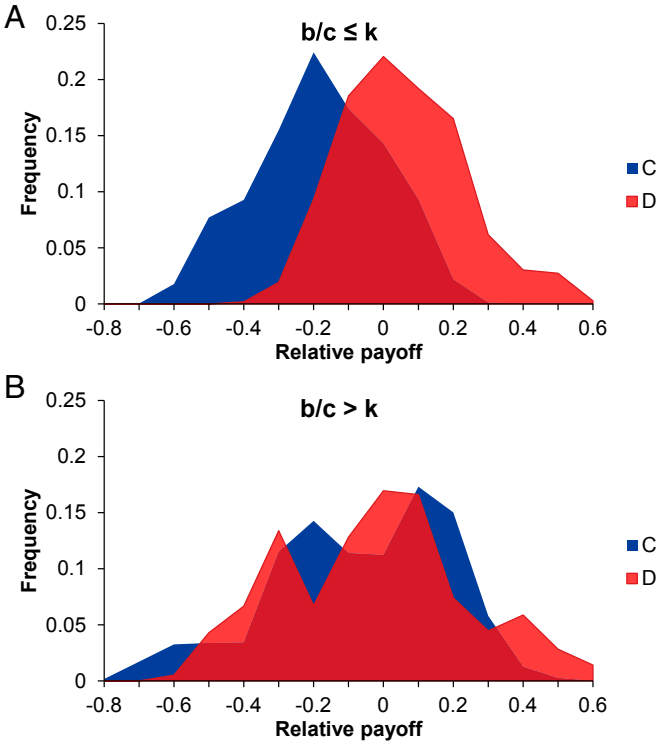

Fig. 5. Defectors (D) significantly out-earn cooperators (C) when b/c ≤ k (*A*), but not when b/c > k (*B*). Shown is the distribution of payoffs relative to average session payoff, with one observation per subject per round, for C (blue) and D (red). To make payoffs comparable across conditions, they are normalized by the maximum possible relative payoff $[bk - ck(N - 1)]/N$, where N is the number of players in the session.

profoundly important role that networks may play in the origins and maintenance of cooperation in human societies.

Our results also help to explain why previous studies concluded that static network structure does not promote cooperation in experiments with human subjects (41–48). We find that the $b/c > k$ condition is required for cooperation to succeed and that this condition was not satisfied in most previous experiments where cooperation failed in networked populations. Traulsen et al. (41) used $b/c = 3$ and a lattice with $k = 4$; Rand et al. (42) used $b/c = 2$ and a random graph with average $k = 3.25$; Suri and Watts (43) used a Public Goods game with an effective $b/c = 2.67$ and various different network structures all having $k = 5$. Other experiments used Prisoner's Dilemma games that are not decomposable into a benefit-to-cost ratio, but can be analyzed using a generalized form of the $b/c > k$ condition [for a general Prisoner's Dilemma game, where a player earns T from defecting while the partner is cooperating, R from mutual cooperation, P from mutual defection, and S from cooperating while the partner is defecting; the condition for cooperation to succeed is $Q^* > k$ with $Q^* = (P + S - R - T)/(R + S - P - T)$ (37)]. Cassar (44) used $Q^* = 4$ and various network structures all having $k = 4$, Grujić et al. (45) used $Q^* = 5.67$ and a lattice with $k = 8$, and Wang et al. (46) used $Q^* = 2.2$ and cliques or random regular graphs with $k = 5$. Thus, the fact that networked interactions did not promote cooperation in any of these experiments is consistent with the theory and our results. It is also important to note that in some of these previous experiments (42–44, 46), participants were not given information about the payoffs of their neighbors, precluding the method of strategy updating which allows cooperation to succeed when the $b/c > k$ condition is satisfied; thus, we would not predict stable cooperation in these settings even with $b/c > k$.

Importantly, the decline of cooperation in these previous network studies shows that the stability we observe when $b/c > k$ is not driven purely by repeated game effects. Even though all of these experiments (as well as our $b/c < k$ treatments) involved repeated interactions between the same fixed neighbors, stable cooperation was not observed [and in experiments that included shuffled control conditions, cooperation was not greater with fixed partners than with shuffled partners (41, 42, 45)]. This failure of cooperation in these repeated games suggests that interaction structure plays a key role in the stability we observe.

There are two previous experiments that did satisfy the theoretical condition and, nonetheless, did not find stable cooperation. However, these studies involved design features that make inference regarding the $b/c > k$ condition difficult. Gracia-Lázaro et al. (47) used $Q^* = 5.67$ and a lattice with $k = 4$ or a heterogeneous network with an average $k = 3.13$, but they ran only a single replicate of each network (yielding only two independent observations). Kirchkamp and Nagel (48) used $b/c = 5$ and networks with $k = 4$ (satisfying the condition) or $k = 10$ (not satisfying the condition), but subjects were given no information about the payoff structure of the game. Instead, they received information each round regarding choices and resulting payoffs for themselves and their neighbors, from which they could try to make inferences about the payoff structure. Thus, it seems likely that subjects in this experiment may have engaged in a high degree of experimentation in an effort to understand the game, and experimentation undermines the ability of networks to promote cooperation. (Similarly, subjects in the study by Gracia-Lázaro et al. (47) were high-school students, and thus may have also engaged in more experimentation and nonstrategic behavior than our older subjects).

Issues related to experimentation in network experiments were first emphasized by Traulsen et al. (41), who linked this behavior to the theoretical concept of "exploration dynamics" (54). Experimentation was defined as switching to a strategy not currently played by any of one's neighbors (a process similar to mutation in evolutionary models). Exploration/mutation disrupts the clustering of cooperators, because a player surrounded by cooperators might spontaneously switch to defection. Thus, theory predicts that, as the mutation rate increases, the b/c required to maintain cooperation rises above k (40). It may be that by concealing the payoff structure from subjects, Kirchkamp and Nagel (48) induced a rate of exploration large enough to derail cooperation even with $b/c = 5$ and $k = 4$.

What, then, is the role of exploration in our data? We find that defectors with all defecting neighbors switch to cooperation 15.7% of the time when $b/c \leq k$ and 17.4% of the time when $b/c > k$, a nonsignificant difference ($P = 0.464$). Thus, "mutations" from defection to cooperation, which do not prevent the clustering of cooperators, are common in both cases. However, spontaneous changes from cooperation to defection are significantly less common when $b/c > k$ compared with $b/c \leq k$ ($P = 0.010$). Cooperators with all cooperating neighbors switch to defection 14.1% of the time when $b/c \leq k$, but only 5.1% of the time when $b/c > k$. Importantly, this 5.1% mutation rate is low enough that the success of cooperation in our $b/c > k$ experimental conditions comports well with theoretical predictions, even taking into account exploration/mutation (with a 5.1% mutation rate, $b/c > 3.35$ is required for $k = 2$ and $b/c > 4.99$ is required for $k = 4$, both of which are satisfied by our relevant $b/c > k$ conditions; *SI Appendix*). Moreover, these results suggest that the extremely high exploration rates observed by Traulsen et al. (41) may have been the result of subjects (correctly) judging those game settings as unfavorable to cooperation. Exploring the evolutionary dynamics of strategies that can modify their mutation rates across settings is an important direction for future work.

An important limitation of the extant theory generating the $b/c > k$ condition is that it does not take into account expected game length (in the case of "indefinitely repeated" games with uncertain ending conditions) or end-game effects (in the case of "finitely repeated" games of known length). The reason is that the theory assumes very simplistic agents who merely copy their neighbors proportional to payoff, without engaging in any more complex strategic thinking. Thus, these agents' decisions are unaffected by game length/ending. However, previous experimental work shows that expected game length has a notable effect on cooperation in pairwise (non-networked) repeated games (10, 17, 55), and end-game effects (where participants begin defecting as the end of a finitely repeated game approaches) have been found in a wide range of settings, including games on networks (46, 56–58). Thus, exploring how game length effects interact with payoffs and network structure is an important direction for future experimental work.

The success of the $b/c > k$ condition in predicting experimental play in our repeated games, despite its derivation in the context of unconditional strategies (33), suggests that this theory may have wider implications than previously conceived. Perhaps when players are informed of the payoffs of others, they focus on this information when choosing C or D, rather than reciprocating neighbors' behavior (as prescribed by typical strategies from repeated games theories). There may also be rationales for the $b/c > k$ criterion that come from behavioral models or myopic learning models in addition to the evolutionary model in which it was first derived, or from update rules other than the rules assumed by the particular evolutionary theory that originally generated the $b/c > k$ rule (33). For example, when $b/c > k$ is satisfied, cooperators need only one cooperative neighbor to "break even" (i.e., to earn more than the zero payoff they would earn if they had not played the game or if they had played in a group where all players defected). Thus, the $b/c > k$ condition may be relevant for agents who, rather than maximizing their payoff through imitation as in most evolutionary models, engage in a variant of conditional cooperation (59), where they cooperate as long as doing so does not make them worse off than the baseline reference point. For similar reasons, the $b/c > k$ condition may also be relevant for learning models that seek a "satisficing" payoff, rather than a maximal payoff (60). Further exploration of these possibilities, as well as other behavioral and learning models (49, 50), is a promising direction of future study.

Experimentally manipulating the cooperative dynamics of the network, for example, by using artificial agents that evince particular strategies, and thus help stimulate the emergence and maintenance of cooperative clusters, will also be instructive. So too will looking at how our findings for cycles with different numbers of neighbors extend to other network structures.

Our results suggest that regularity in network structure can contribute to cooperation, and this effect may help to explain why such structures exist and have been maintained. They also emphasize the important role that even static networked interactions can play in our social world and suggest that it may be possible to construct social institutions that foster improvements in collaboration simply by organizing who is connected to whom.

Methods

Experimental Design. Subjects are arranged on a ring and connected to one, two, or three neighbors on each side (k = 2, 4, or 6 total neighbors). They begin with 100 points in their account and then play a repeated cooperation game. In each round, they can choose D by doing nothing or C by paying a cost of $c = 10 * k$ points to give all k neighbors a benefit of b points (b = 20, 40, or 60). Thus, subjects make a single cooperation decision and cannot selectively opt for cooperation with some neighbors but not others (making the game closer to a repeated Public Goods game than a repeated Prisoner's Dilemma game). Following each decision, subjects are informed of the decisions of each of their neighbors, as well as the total payoff for the round earned by themselves and by each neighbor.

Subjects begin by reading the instructions and then play one practice round that does not count toward their final payoff. Positions in the network are then rerandomized, and subjects proceed to play the game for 50 rounds in experiment 1 and 15 rounds in experiment 2. In experiment 1, we were not concerned about end-game effects because, over 50 rounds, it is difficult to keep track of exactly which round one is in, and therefore to know which round is the final round. In experiment 2, however, the game was much shorter; therefore, subjects are not informed about the game length to simulate an infinitely repeated game (as in ref. 19). If a subject drops out of the game in experiment 2 at some point (an issue that is much more pronounced in online experiments compared with traditional laboratory experiments), her spot on the ring is eliminated and her neighbors are rewired accordingly (although they are not notified of this change to minimize the disruption caused by the dropout).

Recruitment: Experiment 1. Subjects in experiment 1 were recruited from the Yale University School of Management's subject pool. Subjects participated in the experiment at the Yale University School of Management's behavioral laboratory, consisting of 12 visually partitioned computers. Subjects read instructions on the computer and then interacted via custom software designed to implement our game in the laboratory.

Subjects received a $10 fixed rate for completing the experiment, plus an additional $1 for every 300 points earned during the game (mean additional earnings of $11.92 from the game: minimum of $3 and maximum of $18). Instructions and screenshots of the game interface are provided in *SI Appendix*.

Experiment 1 has two treatments. In the network treatment, subjects play with the same partners for 50 rounds. In the well-mixed treatment, subjects' positions on the ring are reshuffled before each of the 50 rounds, destroying the possibility for assortment to arise. We ran 13 sessions over the course of 2 d. To preserve random assignment to condition, we alternated sessions on each day between the network treatment (seven sessions in total) and the well-mixed treatment (six sessions in total); thus, there was no systematic variation between treatments in terms of date or time of day at which the experiments were carried out. In total, we recruited n = 109 subjects. The number of subjects per session did not vary significantly across treatments (χ^2 test, P = 0.413).

For completeness, we note that two additional well-mixed sessions were run on a separate day (an additional 17 subjects), but because no corresponding network treatments were run on that same day, these sessions violated our random assignment scheme. Therefore, we do not include them in our analyses. Including these extra well-mixed sessions, however, does not qualitatively change our results: We still find stable cooperation in the network treatment (because including the extra well-mixed sessions does not change these data), and we still find significantly more cooperation in the network treatment compared with the well-mixed treatment in the second half (P = 0.010), last third (P = 0.008), and last quarter (P = 0.010) of the game (note that these results actually become more statistically significant when including the randomization-violating treatments).

Recruitment: Experiment 2. Subjects in experiment 2 were recruited online using AMT (43, 52, 61) and redirected to an external website where our experimental was implemented. AMT is an online labor market in which employers contract with workers to complete short tasks for relatively small amounts of money. Workers are paid a fixed baseline wage (show up free for experiments) plus an additional variable bonus (which can be conditioned on their performance in the game).

AMT and other online platforms are extremely powerful tools for conducting experiments, allowing researchers to recruit easily and cheaply a large number of subjects who are substantially more diverse than typical college undergraduates. Nonetheless, there are potential issues in online experiments that either do not exist in the physical laboratory or are more extreme [a detailed discussion is provided by Horton et al. (52)]. Most notably, experimenters have substantially less control in online experiments, because subjects cannot be directly monitored as in the traditional laboratory. Thus, multiple people might be working together as a single subject or one person might log on as multiple subjects simultaneously (although AMT goes to great lengths to prevent multiple accounts and, based on Internet Protocol address monitoring, it happens only rarely). One might also be concerned about the representativeness of subjects recruited through AMT, although they are substantially more demographically diverse than subjects in the typical college undergraduate samples.

To address these potential concerns, numerous recent studies have explored the validity of data gathered using AMT [an overview is provided by Rand (61)]. Most relevant here are two direct replications using economic games, demonstrating quantitative agreement between experiments

conducted in the physical laboratory and experiments conducted using AMT with ~10-fold lower stakes in a repeated Public Goods game (43) and a one-shot Prisoner's Dilemma (52). It has also been shown that play in one-shot Public Goods games, Trust games, Dictator games, and Ultimatum games on AMT using $1 stakes is in accordance with behavior in the traditional laboratory (62).

Consistent with standard wages on AMT, subjects received a $3 fixed rate for completing the experiment, plus an additional $0.01 for every 10 points earned during the game [average additional earnings of $0.93 (SD = $0.83) from the game: minimum of $0 and maximum of $4.62]. Experimental instructions and screenshots of the game interface, as well as participant demographics, are provided in *SI Appendix*.

In total, we have nine main treatments: [$k = 2$, $k = 4$, $k = 6$] × [$b/c = 2$, $b/c = 4$, $b/c = 6$]. In these treatments, subjects play with the same partners for 15 rounds. We also include additional control conditions where subjects' positions on the ring are reshuffled before each of the 15 rounds, destroying the possibility for assortment to arise. Our design has three such controls, one for each [b,k] combination satisfying $b/c > k$ (i.e., $k = 2$, $b = 4$; $k = 2$, $b = 6$; $k = 4$, $b = 6$).

For each treatment, we ran four sessions, for a total of 48 sessions. Each session consisted of 24.2 subjects on average (minimum of 15 players and maximum of 34 players), for a total of 1,163 participants. The number of subjects per session did not vary significantly across treatments (χ^2 test, $P = 0.321$). An average of 1.38 subjects per session had dropped out by the final round (minimum of zero players and maximum of five players). The number of players dropping out did not vary significantly across treatments (χ^2 test, $P = 0.771$).

ACKNOWLEDGMENTS. We thank Mark McKnight for creating the software used in the experiments; Robert Kane for assistance in running the experiments; Benjamin Allen for useful theoretical insights; and Drew Fudenberg, Jillian Jordan, and Arne Traulsen for helpful feedback on earlier drafts. This research was supported by the John Templeton Foundation and a grant from the Pioneer Portfolio of the Robert Wood Johnson Foundation.

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Supporting Information

for

Static network structure can stabilize human cooperation

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Contents

Theoretical motivation for the *b/c>k* condition

The *b/c>k* condition comes from a theory of imitation dynamics (e.g. evolutionary game theory) on networks (1). Here we sketch the intuition underlying the *b/c>k* result; we refer readers to (1) for technical details.

The theory works as follows. Each player has a strategy, either cooperate (C) or defect (D). Players sometimes change their strategy by copying a neighbor's strategy. When this happens, a neighbor is picked proportional to payoff in the previous round to be copied (i.e. if my strategy is C, and I have a D neighbor with a high payoff and a C neighbor with a low payoff, then I am more likely to switch to D; or if I am a D player with a high payoff C neighbor and low payoff D neighbor, I am more likely to switch to C). In this way, the fraction of cooperators and defectors in the population evolves over time.

It has been shown by (1) that cooperation can spread under this framework as long as *b/c>k*, which causes the network structure to generate enough clustering to make cooperators earn high payoffs. To gain an intuition for this result, consider a *k*=2 cycle with perfect assortment (Figure S1).

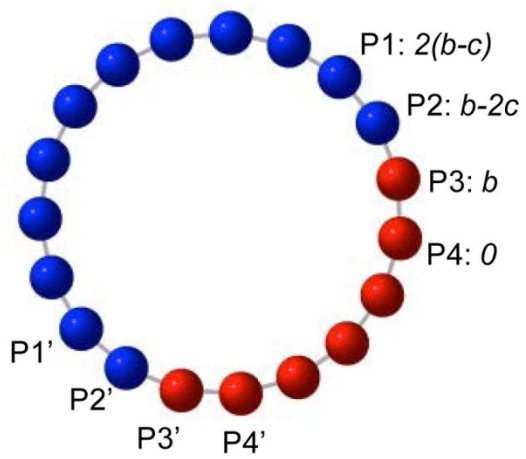


Figure S1. A k=2 cycle with perfect assortment. Blue = C, red = D. Payoffs of players P1-P4 and P1'-P4' are indicated.

Under the dynamic described above, in which players copy their neighbors, the only way the frequency of cooperation can change is if a player on the edge between clusters (i.e. players P2, P3, P2', or P3' in Figure S1) changes strategy; the reason is that, for people on the interior of a cluster, they and both neighbors are playing the same strategy and so imitation cannot lead to a change.

If P2 or P2' compare the payoffs of their neighbors, they see that the cooperator earns *2(b-c)* whereas the defector earns *b*; thus if *b/c*>2, they are more likely to copy the cooperator (and cooperation will spread on average). Similarly, if P3 or P3' compare the payoffs of their neighbors, they see that the cooperator earns *b-2c* whereas the defector earns 0; thus, again if

$b/c>2$, they are more likely to copy the cooperator. Thus for cycles, with $k=2$, $b/c>2$ is required for players to preferentially imitate cooperation (and therefore for cooperation to spread). A generalization of this logic yields the $b/c>k$ condition for cases with $k>2$ (1).

As described above, under this update rule ('death birth updating'), a player with the same strategy as all of her neighbors cannot change strategy when updating (since whichever of her neighbors is picked will result in the strategy she is already playing). If such a change does occur, it is referred to as exploration or 'mutation'. See below for a detailed discussion of the effect of mutation on networked cooperation.

Statistical details

Here we provide regression tables to accompany the statistics reported in the main text. Note that all regressions cluster standard errors on subject and session to account for the non-independence of repeated observations from the same subject, and from different subjects within the same session.

Experiment 1

Table S1. Cooperation in all rounds as a function of round, well-mixed indicator, and the interaction between the two. The non-significant coefficient on Round indicates no change over time in the networked condition (where Well-Mixed=0). Evaluating the net coefficient on Round for the Well-Mixed condition (i.e. coeff on Round + coeff on [Well-Mixed X Round]) gives coeff=-0.0123, p=0.053. Logistic regression clustered on subject and session.

	(1)
Well-Mixed	-0.0984
	(0.445)
Round	0.00521
	(0.00492)
Well-Mixed X Round	-0.0175*
	(0.00805)
# Players	0.207**
	(0.0762)
Constant	-0.853
	(0.805)
Observations	5,450

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S2. Cooperation by Well-mixed. Initially, cooperation does not vary, but later in the session there is significantly less cooperation when the population is well-mixed; this is true when considering the last half (rounds 26-50), last third (34-50) or last quarter (38-50). Logistic regression with robust standard errors clustered on subject and session.

	(1) Round 1	(2) Round 26-50	(3) Round 34-50	(4) Round 38-50
Well-mixed	0.210	-0.849*	-0.948*	-0.891*
	(0.550)	(0.411)	(0.429)	(0.418)
# Players	0.398	0.150**	0.169**	0.172**
	(0.209)	(0.0578)	(0.0605)	(0.0632)
Constant	-2.114	-0.0946	-0.219	-0.357
	(1.735)	(0.596)	(0.615)	(0.619)
Observations	109	2,725	1,853	1,417

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

We note that these results are robust to a more conservative analysis in which we treat each session as a single data point (with value equal to the average frequency of cooperation over that session), and compare conditions using the non-parametric Wilcoxon Rank-sum test: comparing the average cooperation rates in the Networked and Well-mixed conditions shows no difference in round 1 (p=0.38), and significantly more cooperation in the Networked condition in the second half (p=0.0321), last third (p=0.0321), and last quarter (p=0.0319) of the game.

Experiment 2

Table S3. Cooperation in the later part of the game as a function of round: cooperation is stable for b/c>k but decreases in b/c≤k. Logistic regression clustered on subject and session. Models 1 and 2 are reported in the main text (second half of the game, rounds 9-15). Models 3 and 4 show that the results are robust to defining the second half the game as being rounds 8-15. Models 5 and 6 show that the results are robust to considering the last third of the game (rounds 11-15) instead of the second half.

	(1)	(2)	(3)	(4)	(5)	(6)
	Rounds 9-15		Rounds 8-15		Rounds 11-15	
	b/c>k	b/c≤k	b/c>k	b/c≤k	b/c>k	b/c≤k
Round	-0.00401	-0.0387*	-0.0218	-0.0400**	0.0109	-0.0556*
	(0.0197)	(0.0176)	(0.0145)	(0.0149)	(0.0341)	(0.0269)
# Players	0.0324	-0.00342	0.0328	-0.00472	0.0350	0.00280
	(0.0443)	(0.0278)	(0.0429)	(0.0283)	(0.0440)	(0.0279)
Constant	-0.595	0.0486	-0.373	0.0956	-0.861	0.129
	(1.121)	(0.703)	(1.057)	(0.714)	(1.156)	(0.624)
Observations	1,916	3,643	2,192	4,173	1,366	2,593

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S4. Cooperation in all rounds as a function of round and b/c>k indicator. Change in cooperation over round differs significantly between b/c>k and b/c≤k. Data from all rounds is included here. Model 2 demonstrates that this effect is not driven by b/c alone. Logistic regression clustered on subject and session.

	(1)	(2)
b/c>k	0.249	0.0287
	(0.200)	(0.214)
Round	-0.0700***	-0.0905***
	(0.00803)	(0.0186)
b/c>k X Round	0.0368**	0.0269**
	(0.0115)	(0.00941)
# Players	0.00312	0.00953
	(0.0224)	(0.0205)
b/c		0.105
		(0.0584)
b/c X Round		0.00572
		(0.00374)
Constant	0.243	-0.251
	(0.537)	(0.561)
Observations	12,093	12,093

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S5. Cooperation in round 1 and round 15 by b/c>k. Initially, cooperation does not vary, but at the end of the game, there is significantly more cooperation when b/c>k. Logistic regression with robust standard errors clustered on subject and session.

	(1) Round 1	(2) Round 1	(3) Round 15	(4) Round 15
b/c > k	0.176	-0.00168	0.701**	0.446*
	(0.203)	(0.222)	(0.230)	(0.225)
# Players	0.00754	0.0112	0.0316	0.0372
	(0.0264)	(0.0247)	(0.0269)	(0.0267)
b/c		0.0871		0.130*
		(0.0502)		(0.0623)
Constant	0.280	-0.0932	-1.328*	-1.902**
	(0.609)	(0.545)	(0.657)	(0.709)
Observations	840	840	787	787

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

We note that similar results are obtained using only one observation per session with Wilcoxon Rank-sums. We find significantly more cooperation in Round 15 when $b/c>k$ than $b/c\leq k$ (Rank-sum, p=0.004), $b/c=k$ (Rank-sum, p=0.006) or $b/c<k$ (Rank-sum, p=0.033); and no significant difference between $b/c=k$ and $b/c<k$ (p=0.45).

Table S6. Level of assortment by b/c>k. Assortment is defined as a cooperator's average number of cooperative neighbors minus a defector's average number of neighbors. As assortment is a session-level characteristic rather than an individual level characteristic, we have 1 observation per session per round. The constant in Model 1 indicates the estimate for assortment when b/c≤k (not significantly different from zero). To estimate the level of assortment when b/c>k, we evaluate the net coefficient (b/c>k coefficient + constant = 0.142, p=0.0005; significantly greater than 0). Linear regression with robust standard errors clustered on session.

	(1)	(2)	(3)
b/c>k	0.151***	0.135**	0.142**
	(0.0390)	(0.0400)	(0.0414)
b/c			-0.00222
			(0.0115)
k		-0.00776	-0.00665
		(0.00898)	(0.0118)
Constant	-0.00933	0.0269	0.0291
	(0.0125)	(0.0464)	(0.0455)
Observations	539	539	539
R-squared	0.156	0.159	0.159

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S7. Round payoff relative to session average by decision (cooperate or defect) and b/c>k. The dependent variable is the subject's payoff in the current round minus the average payoff of all subjects in that session. To make payoffs comparable across values of b/c and k, we normalize payoffs, dividing by the largest possible relative payoff (a player who receives cooperation from all of her neighbors, earning a payoff bk, relative to the average of a group containing her and N-1 other players all receiving the lowest possible payoff of –ck). We also show that results are qualitatively equivalent without the normalization in models 3 and 4. To evaluate the effect on relative payoff of cooperating when b/c≤k, we examine the Cooperate coefficient in Model 1 (significantly less than 0). To evaluate the effect on relative payoff of cooperation when b/c>k, we test the net coefficient (Cooperate coefficient + b/c>k X Cooperate coefficient = -0.041, p=0.152; not significantly different from 0). Linear regression with robust standard errors clustered on subject and session.

	(1)	(2)	(3)	(4)
			Not	Not
	Normalized	Normalized	Normalized	Normalized
b/c>k	-0.0817***	-0.0598***	-14.92***	-24.44***
	(0.0175)	(0.0159)	(3.228)	(3.938)
Cooperate	-0.238***	-0.370***	-42.78***	-24.70**
	(0.0161)	(0.0242)	(3.823)	(7.492)
b/c>k X Cooperate	0.197***	0.126***	35.85***	47.49***
	(0.0326)	(0.0279)	(5.675)	(6.872)
b/c		-0.0100*		4.368***
		(0.00390)		(1.048)
b/c X Cooperate		0.0384***		-5.595**
		(0.00688)		(2.157)
Constant	0.105***	0.137***	18.91***	5.176
	(0.00659)	(0.0147)	(2.127)	(3.385)
Observations	12,093	12,093	12,093	12,093
R-squared	0.176	0.190	0.162	0.172

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S8. Cooperation in the second half of the game (rounds 9-15) as a function of round, comparing network structured versus well-mixed population, all for b/c>k. Logistic regression clustered on subject and session.

	(1) Structured	(2) Well-mixed
Round	-0.00401	-0.0623**
	(0.0197)	(0.0219)
# Players	0.0324	0.0954*
	(0.0443)	(0.0396)
Constant	-0.595	-1.926
	(1.121)	(1.169)
Observations	1,916	2,216

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S9. Cooperation in all rounds as a function of round and well-mixed indicator. Includes data from all rounds. Logistic regression clustered on subject and session.

	(1)
Round	-0.0332***
	(0.00851)
# Players	0.0710***
	(0.0217)
Well-mixed	-0.0726
	(0.224)
Well-mixed X Round	-0.0303**
	(0.0120)
Constant	-1.170**
	(0.544)
Observations	8,944

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S10. Cooperation in round 1 and round 15 by well-mixed. Initially, cooperation does not vary, but at the end of the game, there is significantly less cooperation when the population is well-mixed. Logistic regression with robust standard errors clustered on subject and session.

	(1) Round 1	(2) Round 15
Well-mixed	-0.168	-0.468*
	(0.198)	(0.220)
# Players	0.0967***	0.0463
	(0.0215)	(0.0285)
Constant	-1.721**	-0.987
	(0.540)	(0.771)
Observations	613	586

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S11. Level of assortment by well-mixed. The constant indicates the estimate for assortment in the network structured population (significantly greater than zero). To estimate the level of assortment when the population is well-mixed, we evaluate the net coefficient (Well-mixed coefficient + Constant = -0.055, p=0.203; not significantly different from 0). Linear regression with robust standard errors clustered on session.

	(1)
Well-mixed	-0.155***
	(0.0387)
Constant	0.141***
	(0.0372)
Observations	360
R-squared	0.143

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S12. Round payoff relative to session average by decision (cooperate or defect) and well-mixed. To evaluate the effect on relative payoff of cooperating in the network structured population, we examine the Cooperate coefficient in Model 1 (not significantly different from 0). To evaluate the effect on relative payoff of cooperation in the well-mixed population, we test the net coefficient (Cooperate coefficient + Well-mixed X Cooperate coefficient = -0.162, p<0.0001). Linear regression with robust standard errors clustered on subject and session.

	(1) Normalized	(2) Not Normalized
Well-Mixed	0.0649***	9.533**
	(0.0181)	(3.070)
Cooperate	-0.0407	-6.924
	(0.0286)	(4.225)
Well-Mixed X Cooperate	-0.121***	-17.88***
	(0.0319)	(5.045)
Constant	0.0234	3.983
	(0.0163)	(2.446)
Observations	8,944	8,944
R-squared	0.051	0.047

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Conditions for the evolution of cooperation on networks with mutation

As described in the main text, in our *b/c>k* conditions, we observe that defectors with all defecting neighbors switched to cooperation 17.4% of the time (D-to-C mutation), and cooperators with all cooperating neighbors switched to defection 5.1% of the time (C-to-D mutation). D-to-C mutations are beneficial for cooperation, as they increase the overall level of cooperation and also have the possibility of creating new clusters of cooperators. It is C-to-D mutations that are potentially harmful for cooperation, as that disrupt cooperative clusters.

Here, we ask what predictions theory makes about the evolution of cooperation in the presence of these levels of mutation, based on the work of (2). Asymmetric mutation rates have not been studied theoretically. Therefore, we make the conservative assumption of a symmetric 5.1% chance of spontaneously changing strategy (neglecting the increased likelihood of defectors switching to cooperators, and biasing our estimate *against* cooperation).

For a cycle with k=2, theory predicts that cooperation will be favored when

$$\frac{b}{c} > \frac{2(1-u)}{1-\sqrt{u(2-u)}}$$

where u is the probability of mutating (defined here as choosing C or D with 50% chance – thus a 5.1% chance of changing strategy in our data is equivalent to u=0.102). Substituting u=0.102 yields a condition of b/c>3.35 for cooperation to be favored on a cycle with k=2, a criterion which is satisfied in both of our k=2 conditions where $b/c>k$ ([b/c=4, k=2] and [b/c=6, k=2]).

Analytical results have not been previous derived for cycles with k>2, but a cycle with k=4 may be well approximated by a Cayley graph of the same degree. Theory predicts that cooperation will be favored on a Cayley graph with degree k when

$$\frac{b}{c} > \frac{2k(1-u)(k-1)}{(k-1)(k-\sqrt{k^2-4(k-1)(1-u)^2})}$$

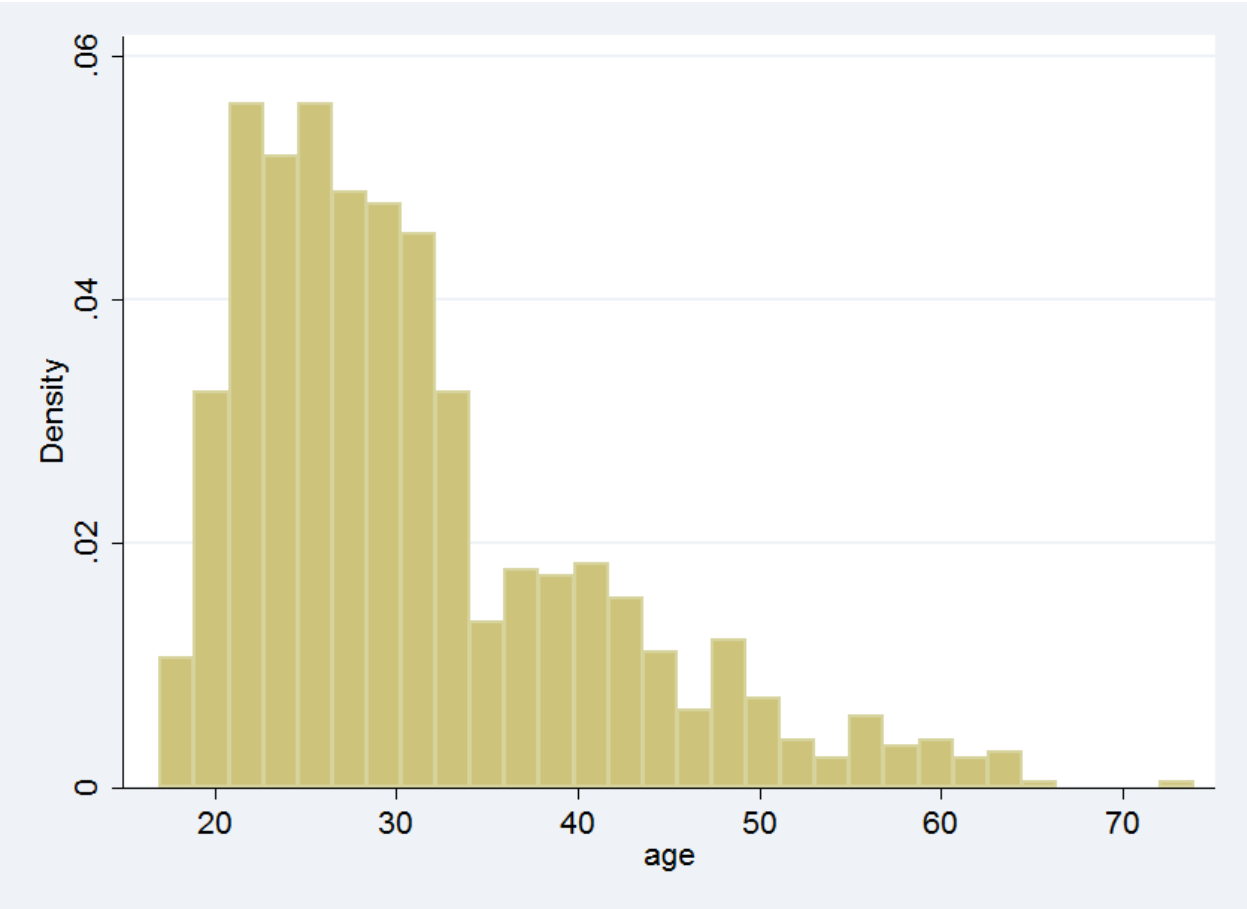
Substituting k=4 and u=0.102 yields a condition of b/c>4.99, which again is satisfied by our k=4 condition where $b/c>k$ (b/c=6, k=4). Thus, the success of cooperation in our $b/c>k$ experimental conditions comports well with theoretical predictions, even taking into account exploration/mutation.

Experiment 2 Participant Demographics

Because the MTurk population is much more diverse than typical undergraduate laboratory populations, we provide background demographics on our MTurk subjects.

Gender: 48.5% female.

Age: Mean 31.1 years old.



Education:

Less than a high school degree	1.0%
Vocational training	3.7%
High school diploma	16.6%
Attended college	28.0%
Bachelor's degree	36.7%
Graduate degree	13.9%
Unknown	0.1%

Annual income:

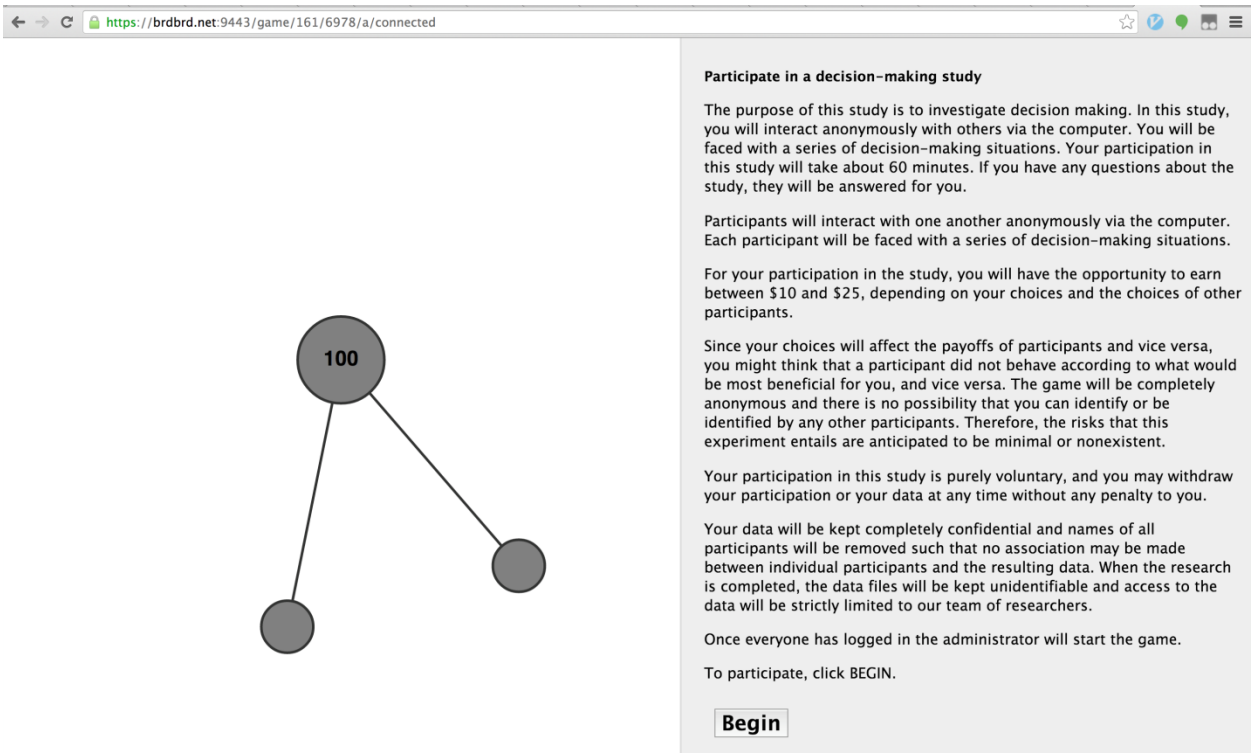
$5,000 or less	17.7%
$5,001 to $10,000	10.4%
$10,001 to $15,000	9.4%
$15,001 - $25,000	13.1%
$25,001 - $35,000	13.9%
$35,001 - $50,000	14.8%
$50,001 - $65,000	9.0%
$65,001 - $80,000	5.2%
$80,001 - $100,000	3.8%
Over $100,000	2.8%

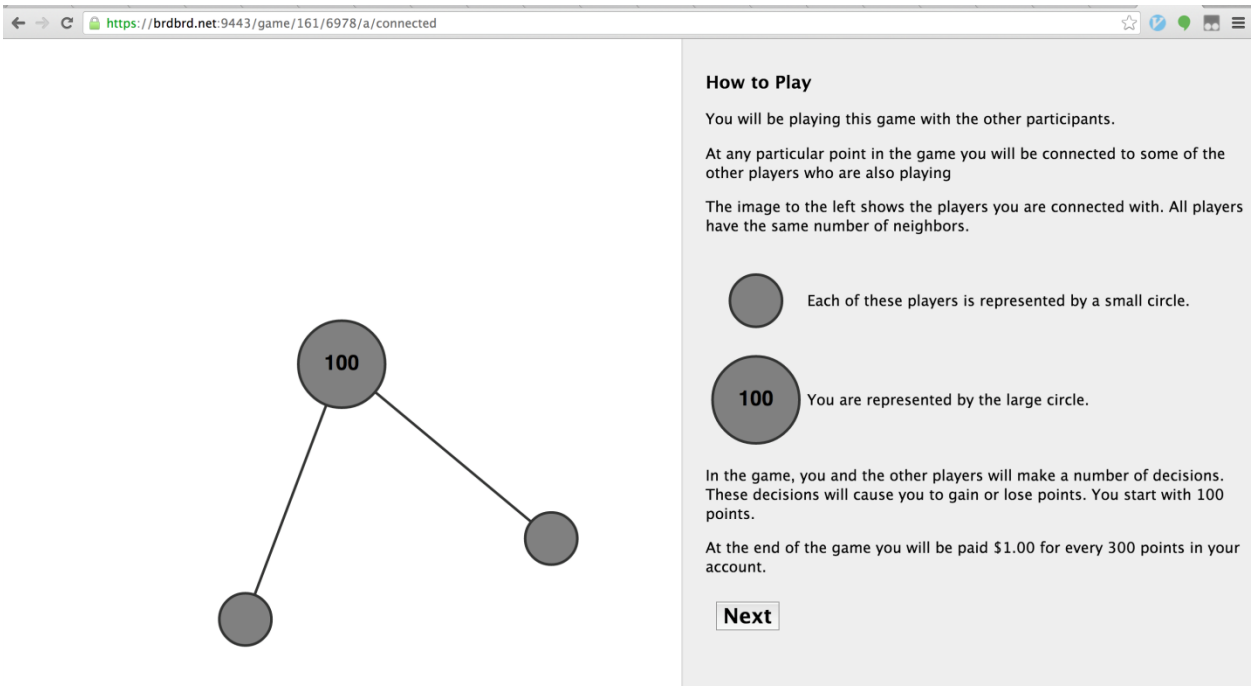
Country of residence:

United States	81.3%
India	11.9%
Canada	1.4%
Romania	0.9%
United Kingdom	0.6%
Macedonia	0.6%
Serbia	0.6%
Croatia	0.3%
Poland	0.3%
Germany	0.2%
Hungary	0.2%
Latvia	0.2%
Mexico	0.2%
Spain	0.2%
Afghanistan	0.1%
Belgium	0.1%
Bosnia and Herzegovina	0.1%
Brazil	0.1%
Dominica	0.1%
Grenada	0.1%
Ireland	0.1%
Italy	0.1%
Jamaica	0.1%
Qatar	0.1%
Russian Federation	0.1%
Singapore	0.1%
Switzerland	0.1%
Taiwan	0.1%
Turkey	0.1%

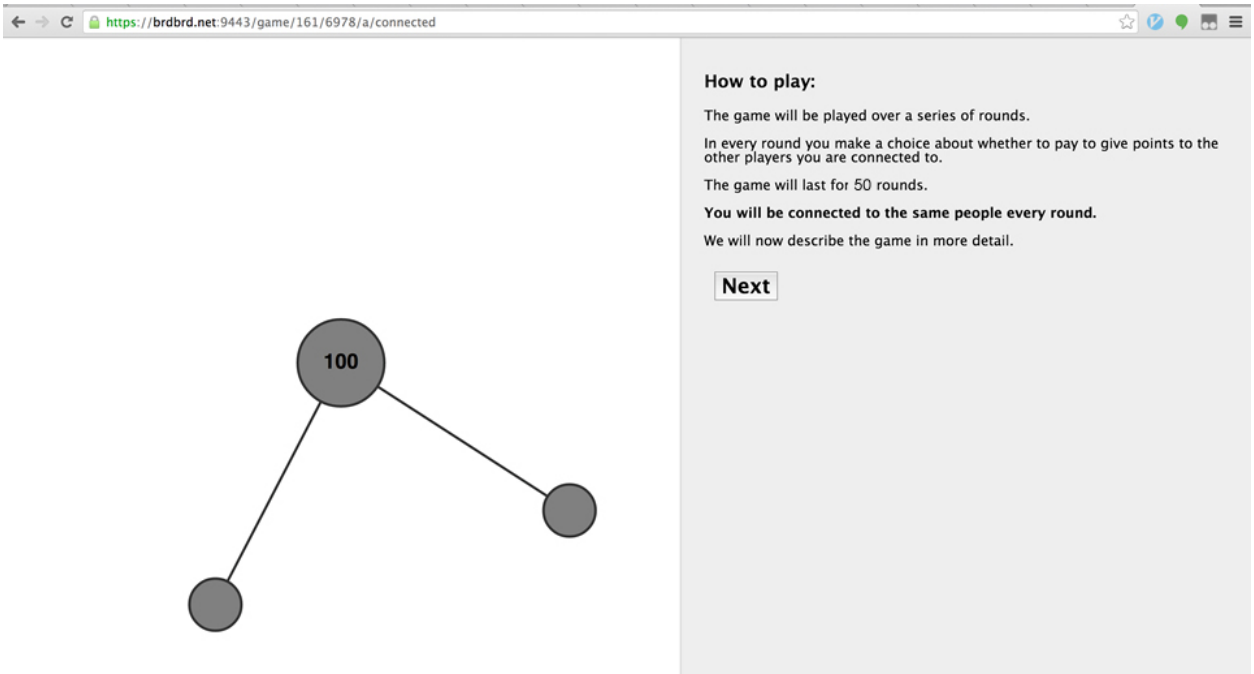
Instructions & screenshots

Experiment 1

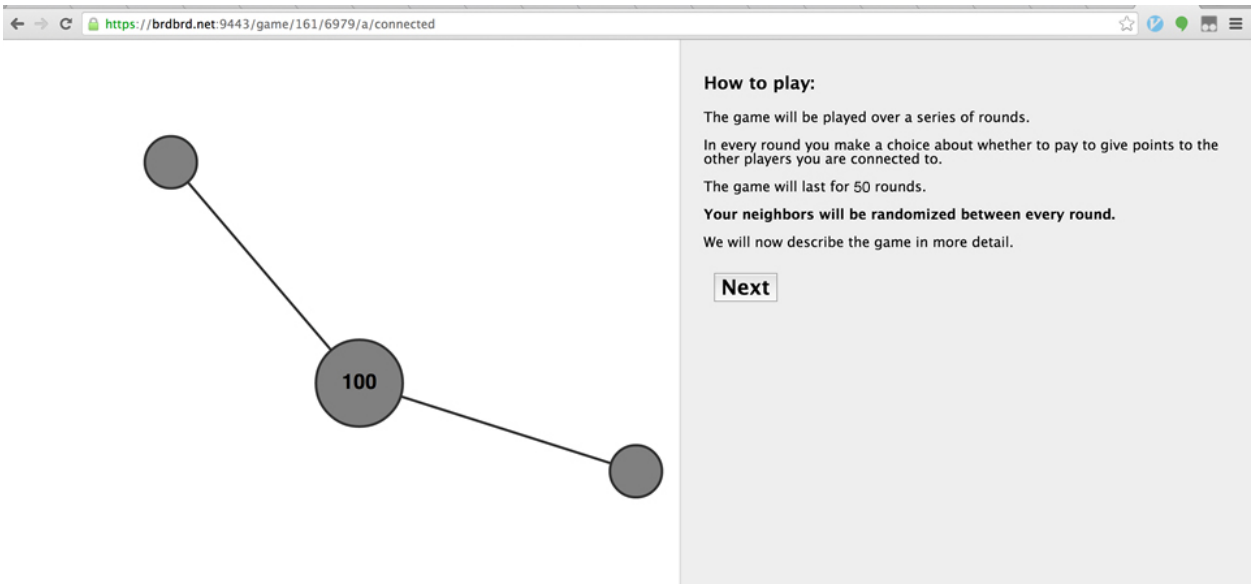


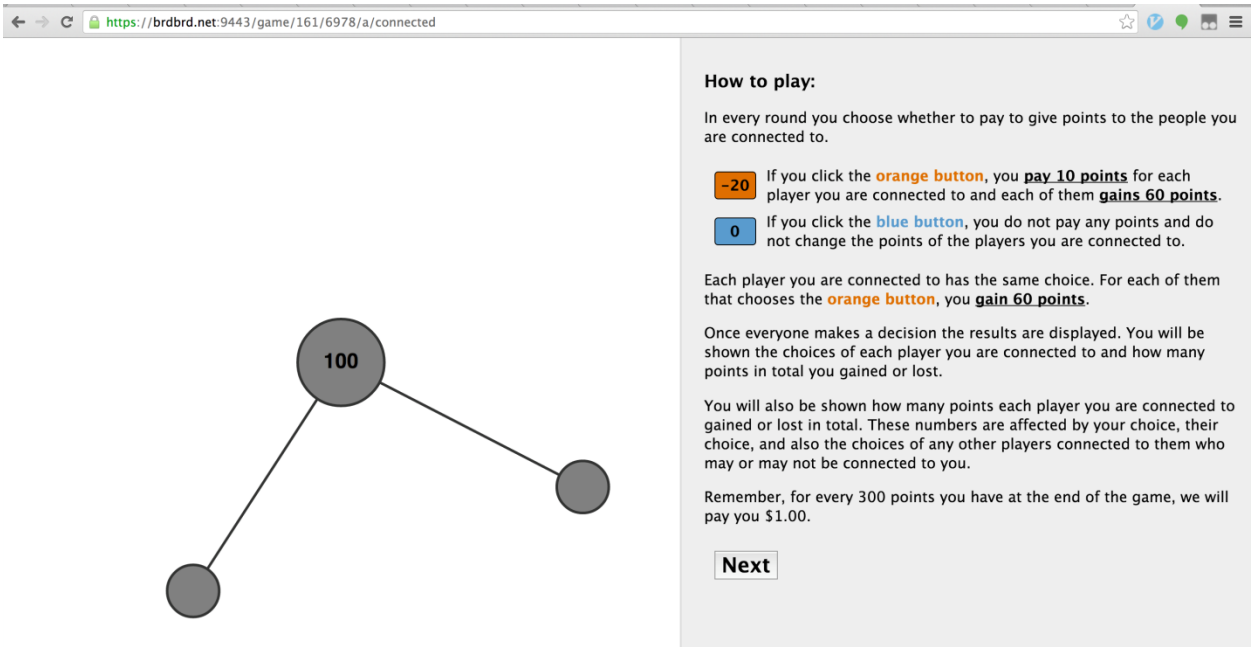


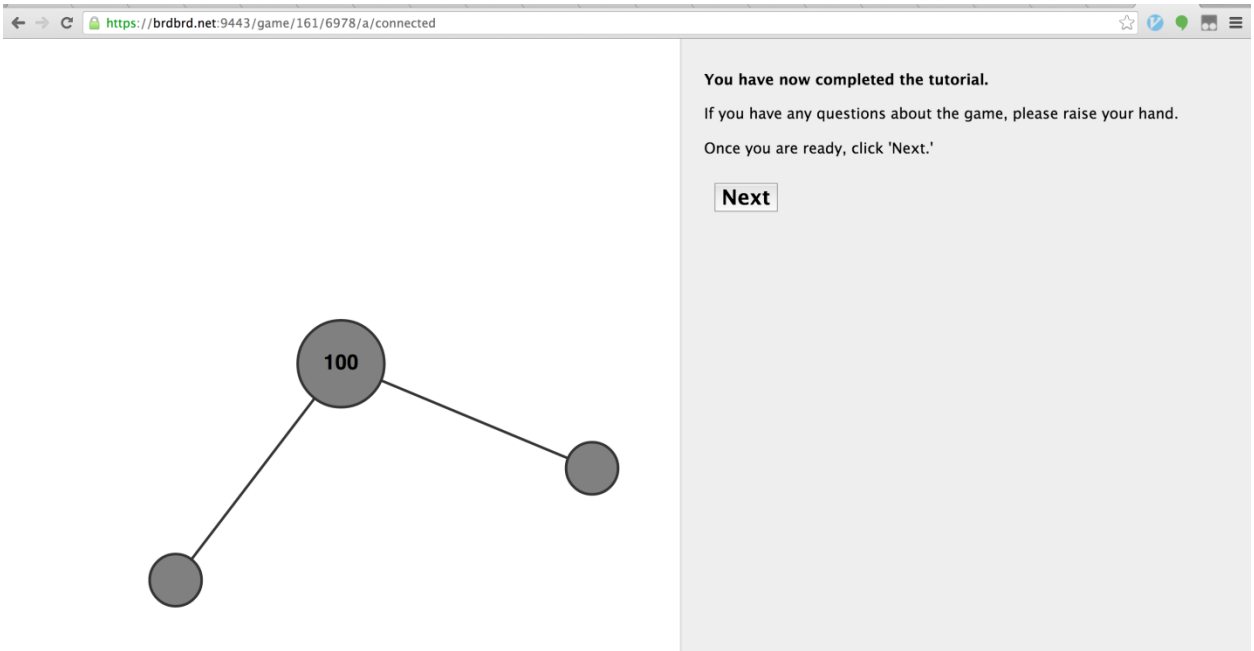
Networked condition:

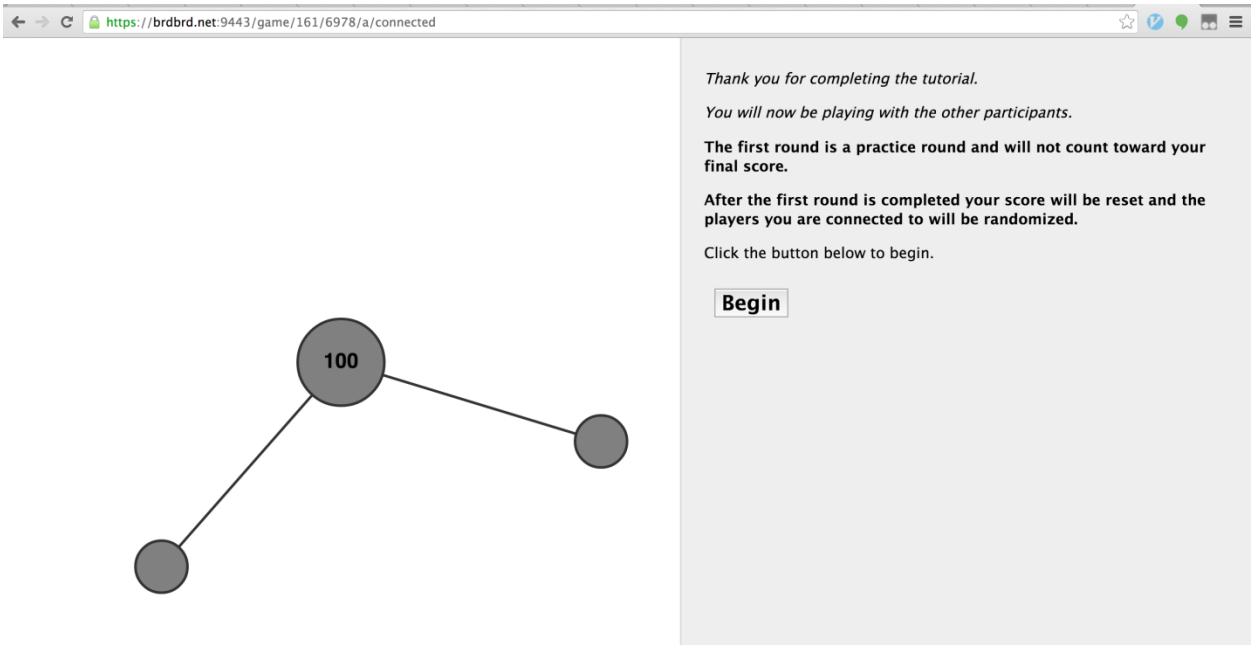


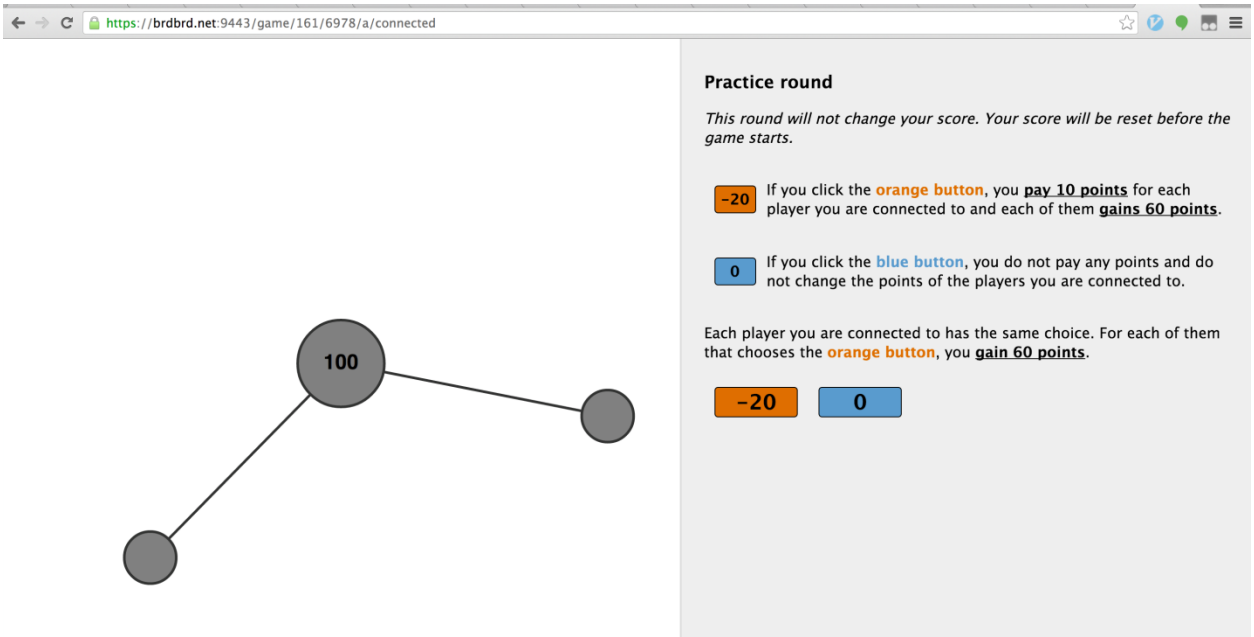
Well-mixed condition:

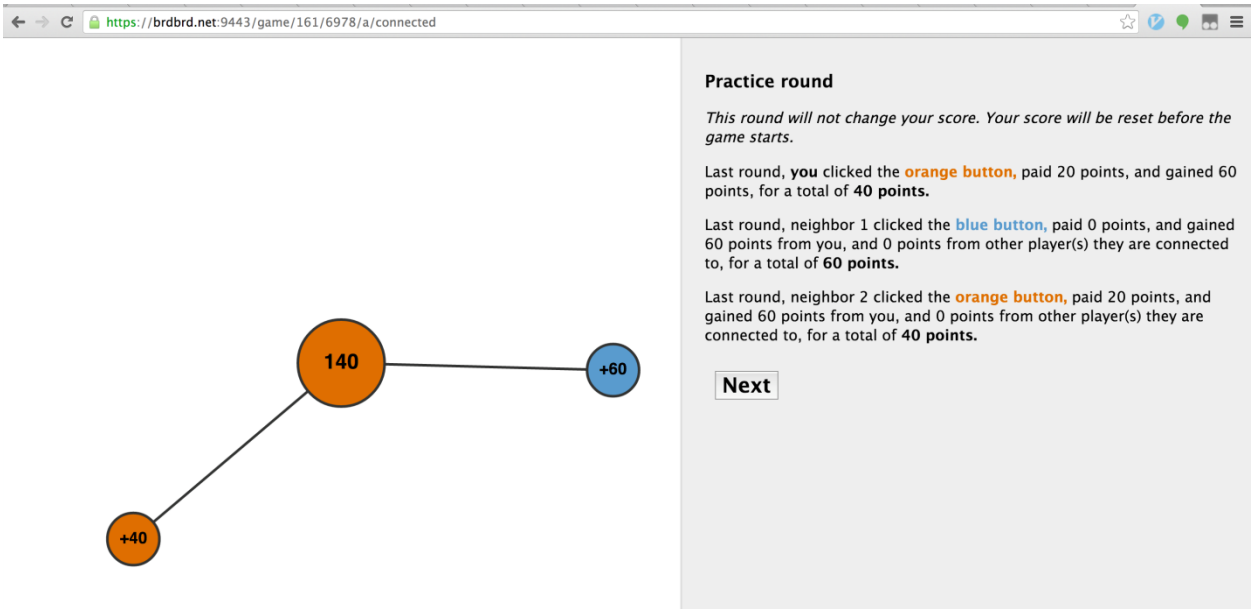


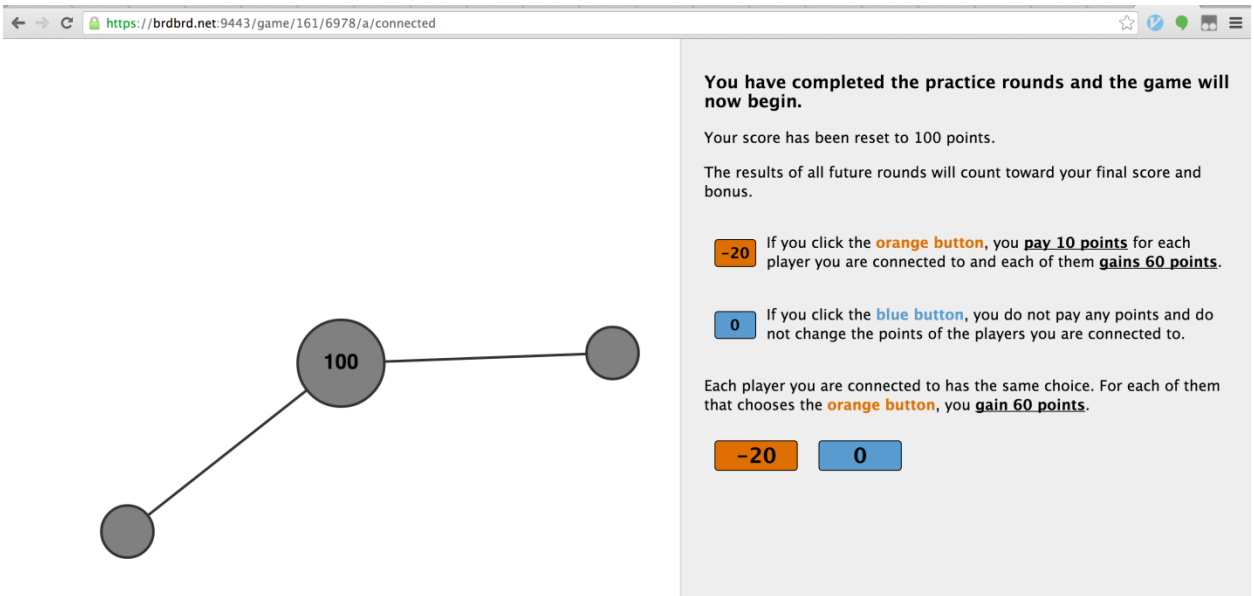

https://brdbrd.net:9443/game/161/6978/a/connected
100
How to play:
In every round you choose whether to pay to give points to the people you are connected to.
-20
If you click the orange button, you pay 10 points for each player you are connected to and each of them gains 60 points.
0
If you click the blue button, you do not pay any points and do not change the points of the players you are connected to.
Each player you are connected to has the same choice. For each of them that chooses the orange button, you gain 60 points.
Once everyone makes a decision the results are displayed. You will be shown the choices of each player you are connected to and how many points in total you gained or lost.
You will also be shown how many points each player you are connected to gained or lost in total. These numbers are affected by your choice, their choice, and also the choices of any other players connected to them who may or may not be connected to you.
Remember, for every 300 points you have at the end of the game, we will pay you $1.00.
Next

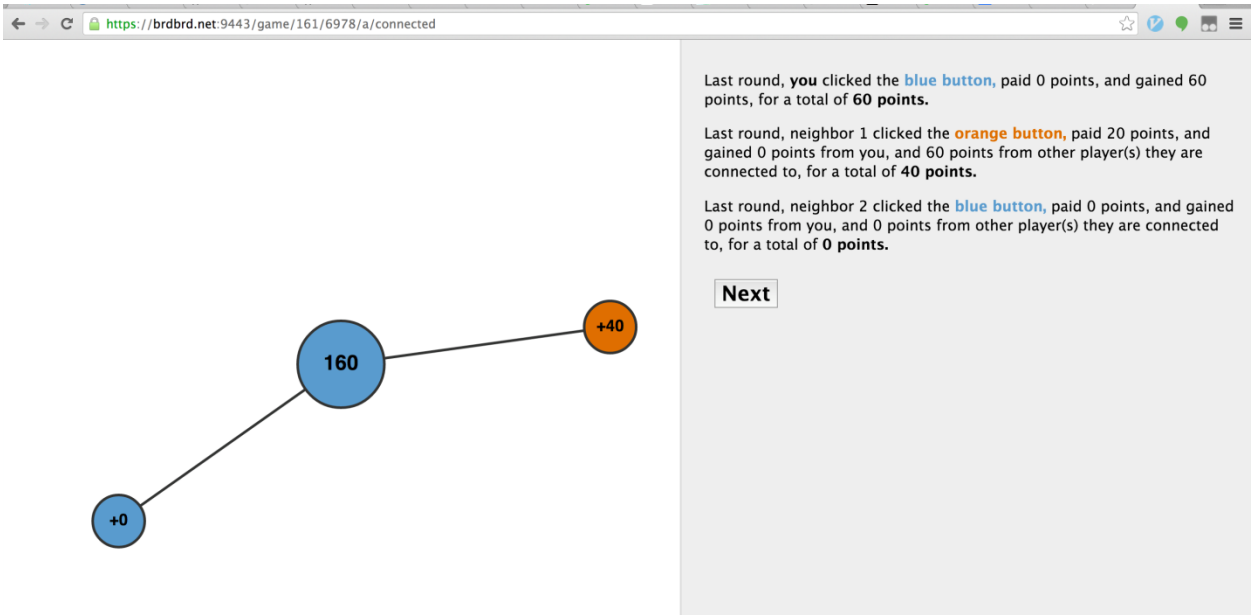

https://brdbrd.net:9443/game/161/6978/a/connected
100
You have now completed the tutorial.
If you have any questions about the game, please raise your hand.
Once you are ready, click 'Next.'
Next

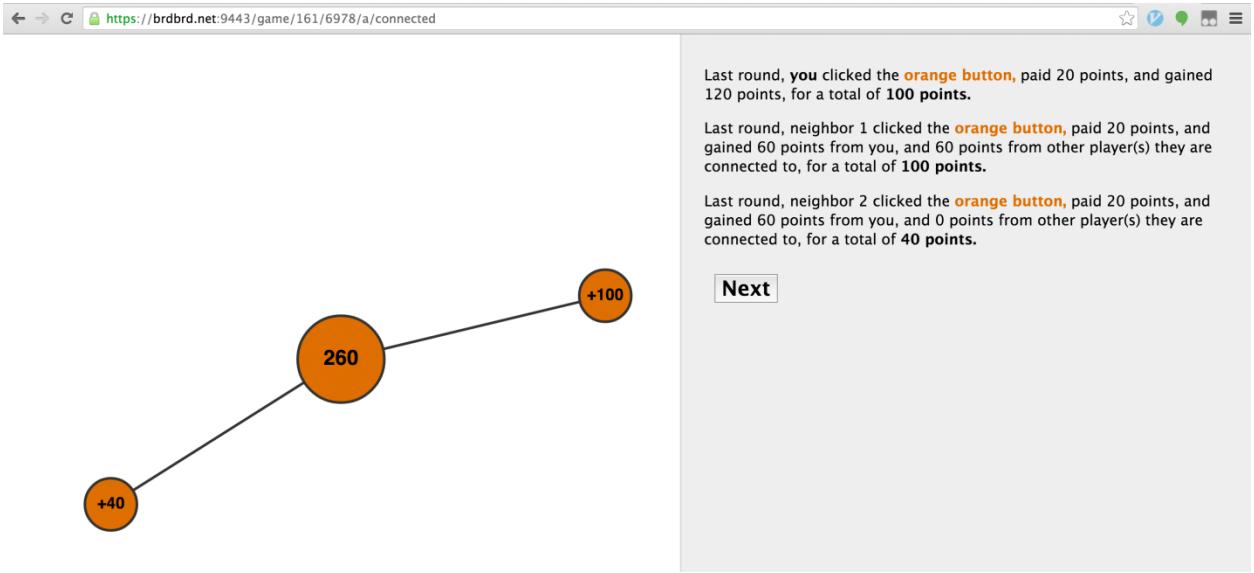

https://brdbrd.net:9443/game/161/6978/a/connected
Thank you for completing the tutorial.
You will now be playing with the other participants.
The first round is a practice round and will not count toward your final score.
After the first round is completed your score will be reset and the players you are connected to will be randomized.
Click the button below to begin.
Begin
100


https://brdbrd.net:9443/game/161/6978/a/connected
Practice round
This round will not change your score. Your score will be reset before the game starts.
-20
If you click the orange button, you pay 10 points for each player you are connected to and each of them gains 60 points.
0
If you click the blue button, you do not pay any points and do not change the points of the players you are connected to.
Each player you are connected to has the same choice. For each of them that chooses the orange button, you gain 60 points.
-20
0
100


https://brdbrd.net:9443/game/161/6978/a/connected
140
+60
+40
Practice round
This round will not change your score. Your score will be reset before the game starts.
Last round, you clicked the orange button, paid 20 points, and gained 60 points, for a total of 40 points.
Last round, neighbor 1 clicked the blue button, paid 0 points, and gained 60 points from you, and 0 points from other player(s) they are connected to, for a total of 60 points.
Last round, neighbor 2 clicked the orange button, paid 20 points, and gained 60 points from you, and 0 points from other player(s) they are connected to, for a total of 40 points.
Next

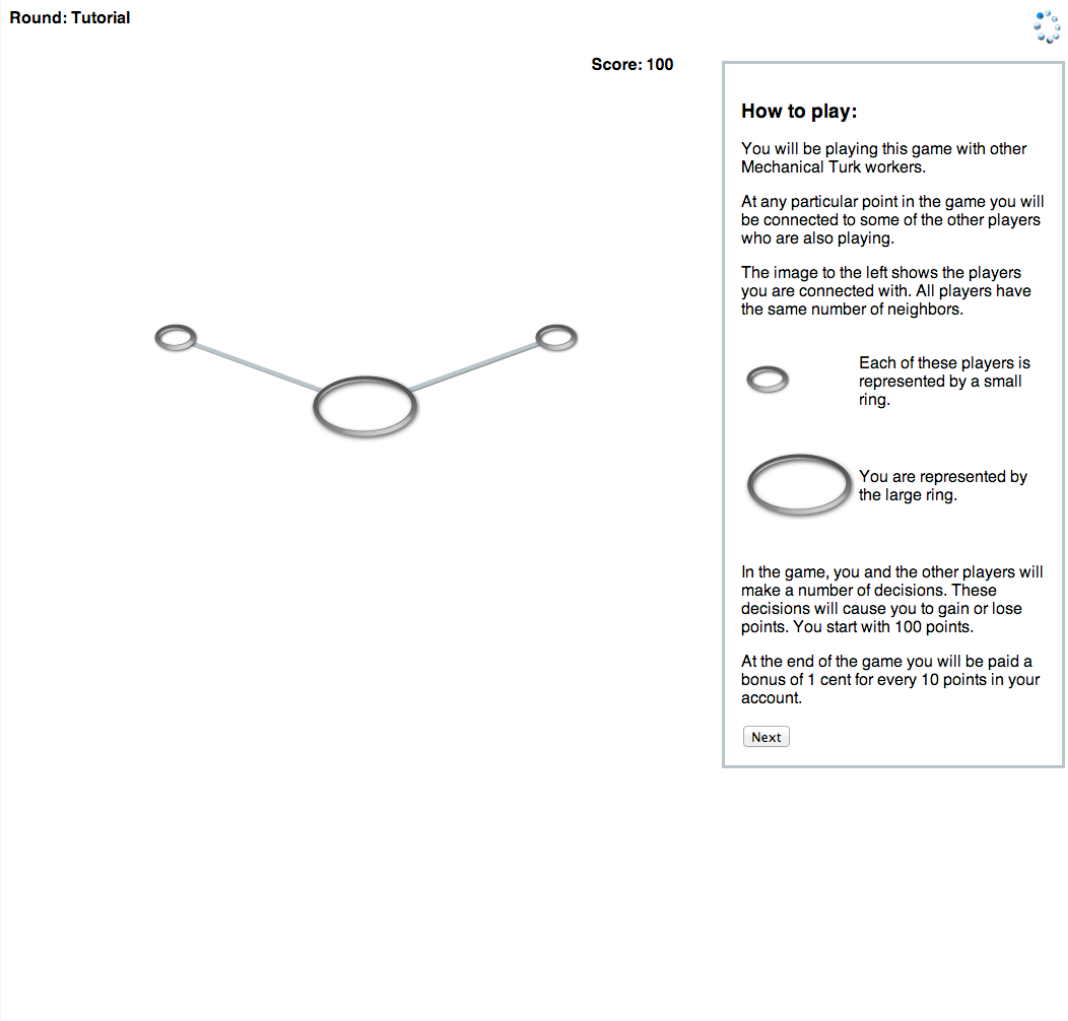

https://brdbrd.net:9443/game/161/6978/a/connected
100
You have completed the practice rounds and the game will now begin.
Your score has been reset to 100 points.
The results of all future rounds will count toward your final score and bonus.
-20
If you click the orange button, you pay 10 points for each player you are connected to and each of them gains 60 points.
0
If you click the blue button, you do not pay any points and do not change the points of the players you are connected to.
Each player you are connected to has the same choice. For each of them that chooses the orange button, you gain 60 points.
-20
0


https://brdbrd.net:9443/game/161/6978/a/connected
Last round, **you** clicked the blue button, paid 0 points, and gained 60 points, for a total of **60 points.**
Last round, neighbor 1 clicked the orange button, paid 20 points, and gained 0 points from you, and 60 points from other player(s) they are connected to, for a total of **40 points.**
Last round, neighbor 2 clicked the blue button, paid 0 points, and gained 0 points from you, and 0 points from other player(s) they are connected to, for a total of **0 points.**
Next
160
+40
+0


https://brdbrd.net:9443/game/161/6978/a/connected
Last round, **you** clicked the orange button, paid 20 points, and gained 120 points, for a total of **100 points.**
Last round, neighbor 1 clicked the orange button, paid 20 points, and gained 60 points from you, and 60 points from other player(s) they are connected to, for a total of **100 points.**
Last round, neighbor 2 clicked the orange button, paid 20 points, and gained 60 points from you, and 0 points from other player(s) they are connected to, for a total of **40 points.**
Next
260
+100
+40

Experiment 2

Here we show sample instructions and play screenshots for Experiment 2, from the networked b/c=6, k=2 game



Round: Tutorial

Score: 100

How to play:

The game will be played over a series of rounds.

In every round you make a choice about whether to pay to give points to the other players you are connected to.

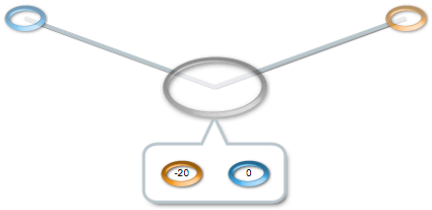
The game will last for an unknown number of rounds. Your actions have no effect on the total number of rounds.

We will now describe the game in more detail.

Next

Round: Tutorial

Score: 100



How to play:

In every round you choose whether to pay to give points to the people you are connected to.

If you click the **orange ring**, you **pay 10 points** for each player you are connected to and each of them **gains 60 points**.

If you click the **blue ring**, you do not pay any points and do not change the points of the players you are connected to.

Each player you are connected to has the same choice. For each of them that chooses the **orange ring**, you **gain 60 points**.

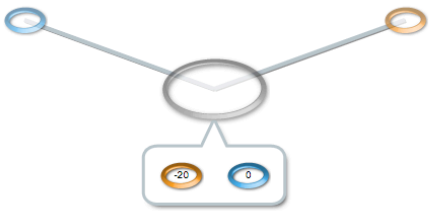
Once everyone makes a decision the results are displayed. You will be shown the choices of each player you are connected to and how many points in total you gained or lost.

Remember, for every 10 points you have at the end of the game, we will add 1 cent to your bonus.

Next

Round: Tutorial

Score: 100



You have now completed the tutorial.

WARNING: This task varies in length between 15 - 30 minutes. To get paid you must actively watch the game screen at all times until the game is completed.

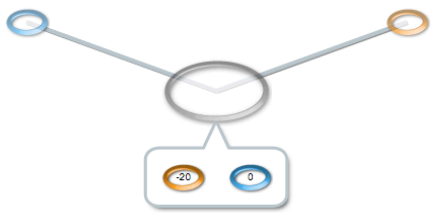
Once the task has begun you must respond to each question without delay. Failure to do so will result in your HIT being rejected and you will not be paid.

If you have understood the material in the tutorial, click 'I Agree' to begin.

I Agree

Round: Tutorial

Score: 100



Thank you for completing the tutorial.

You will now be playing with other Mechanical Turk Workers.

The first round is a practice round and will not count toward your final score.

After the first round is completed your score will be reset and the players you are connected to will be randomized.

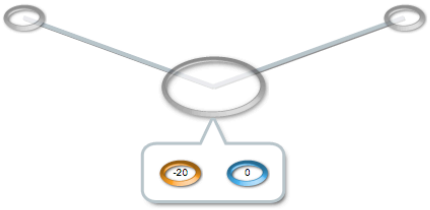
Click the button below to begin.

Begin

Practice Round: Scores will be reset and connections will be randomized at the end of this round.

Round: 1

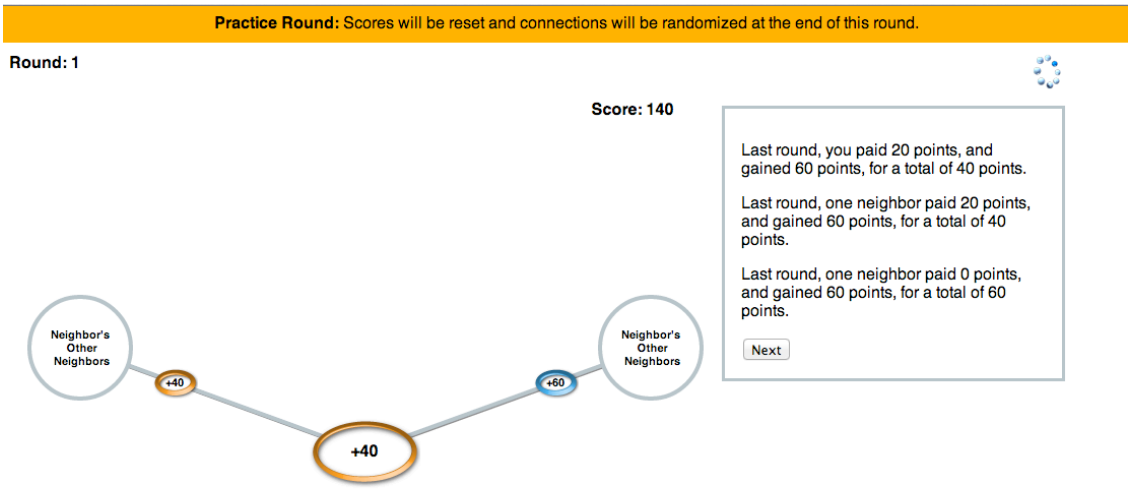
Score: 100



If you click the **orange ring**, you **pay 10 points** for each player you are connected to and each of them **gains 60 points**.

If you click the **blue ring**, you do not pay any points and do not change the points of the players you are connected to.

Each player you are connected to has the same choice. For each of them that chooses the **orange ring**, you **gain 60 points**.



The last two screens then repeated for 15 rounds, without the orange ‘practice round’ header. Note that in this screen, the total payoff for the round of each neighbor is shown, along with the player’s own total payoff for the round.

References

1. Ohtsuki H, Hauert C, Lieberman E, & Nowak MA (2006) A simple rule for the evolution of cooperation on graphs and social networks. *Nature* 441(7092):502-505.
2. Allen B, Traulsen A, Tarnita CE, & Nowak MA (2011) How mutation affects evolutionary games on graphs. *Journal of theoretical biology* 299:97-105.