The effects of reputational and social knowledge on cooperation

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The emergence and sustenance of cooperative behavior is fundamental for a society to thrive. Recent experimental studies have shown that cooperation increases in dynamic networks in which subjects can choose their partners. However, these studies did not vary reputational knowledge, or what subjects know about other’s past actions, which has long been recognized as an important factor in supporting cooperation. They also did not give subjects access to global social knowledge, or information on who is connected to whom in the group. As a result, it remained unknown how reputational and social knowledge foster cooperative behavior in dynamic networks both independently and by complementing each other. In an experimental setting, we show that global reputational knowledge is crucial to sustaining a high level of cooperation and welfare. Cooperation is associated with the emergence of dense and clustered networks with highly cooperative hubs. Global social knowledge has no effect on the aggregate level of cooperation. A community analysis shows that the addition of global social knowledge to global reputational knowledge affects the distribution of cooperative activity: cooperators form a separate community that achieves a higher cooperation level than the community of defectors. Members of the community of cooperators achieve a higher payoff from interactions within the community than members of the less cooperative community.

cooperation | social networks | reputation | social knowledge | experiments

Cooperation among a group of individuals can create a surplus that benefits everyone, but it is often undermined by self-interested incentives to free ride on others’ contributions (1). What drives the emergence of cooperative behavior and how it is possible to sustain it over time are fundamental questions that have been of long-standing interest to social scientists (2). The most common abstract representation of the trade-off individuals face between cooperating and free-riding is the prisoner’s dilemma game, which has been widely studied both theoretically and experimentally (3, 4).

Recent simulation-based (5, 6) and experimental (7–10) studies investigating individuals playing the prisoner’s dilemma game in a group have shown that the ability to form and break connections, and thereby select with whom to play the game, has a significant effect on the level of cooperation. The possibility of forming new connections with cooperative individuals encourages defectors to switch to cooperative behavior even if many of their neighbors are defecting (11). The process of network formation relies on two dimensions of information available to individuals, which we dub reputational and social knowledge. Reputational knowledge is what individuals know about the previous actions of others in the group. Social knowledge is what individuals know about the structure of the social network within the group, which determines who plays the game with whom.

In the context of repeated interactions between two players, reputational knowledge has long been recognized as an important factor in determining cooperation both in theoretical (2, 12, 13) and experimental (2, 14–17) settings. In the two-player case, it is indifferent whether information about the other player’s previous actions comes from a player’s past interaction or from an external reputational mechanism because the two channels coincide. However, this is not the case in a group of individuals in whom the social network determines interactions. If the information about others’ previous actions comes from the social network and indirect communication is infeasible, reputational knowledge will only be available about an individual’s connections, whereas if a reputational mechanism external to the network is present, then an individual will have reputational knowledge about everyone independent of the network. Previous experimental studies have focused on the specific cases in which reputational knowledge is available for either every other individual (7, 9, 10) or only the neighbors (8), and therefore they cannot disentangle whether an external reputational mechanism is necessary for cooperation or whether reputational knowledge available through the social network itself may suffice.

Social knowledge matters in the link formation process because it aids individuals in identifying opportunities in the network (18, 19). For instance, in the context of cooperation, it may help identify loci of cooperative activity in the group, which in turn may have an effect on the aggregate level of cooperation. Surprisingly, the role that differences in the level of social knowledge have in the network formation process, and the influence they have on individual behavior in games on networks, have received little attention in both the theoretical (20) and the experimental (21) literatures. Previous experimental studies about cooperation on networks provide subjects only with information on the identity of their neighbors, and therefore do not investigate the role of social knowledge in determining the network structure and the level of cooperation.

Author contributions: E.G. and C.Y. designed research, performed research, analyzed data, and wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission. M.A.N. is a guest editor invited by the Editorial Board.

Significance

Cooperation is essential for societies to prosper. Recent experiments show that cooperation emerges in dynamic networks in which subjects can select their connections. However, these studies fixed the amount of reputation information available and did not display the network to subjects. Here, we systematically vary the knowledge available to subjects about reputation and the network to investigate experimentally their roles in determining cooperation in dynamic networks. Common knowledge about everyone’s reputation is the main driver of cooperation leading to dense and clustered networks. The addition of common knowledge about the network affects the distribution of cooperative activity: cooperators form a separate community and achieve a higher payoff from within-community interactions than members of the less cooperative community.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1415883112/-/DCSupplemental.
Reputational and social knowledge are not just independent channels but also interact to determine the social network that emerges, and consequently the level of cooperation. Individuals use information about previous actions to decide to whom to connect (9), and therefore the extent of reputational knowledge available may matter in determining the density of the network. As already mentioned, individuals use information about the network to decide to whom to link; for example, they may decide to link to the connections of their neighbors, thereby increasing the level of clustering of the network. The presence of both reputational and social knowledge may combine to further enhance these effects. Previous studies do not vary the level of reputational and/or social knowledge available to subjects, and therefore, in addition to not being able to identify their independent influence, they cannot explore the combined effects of reputational and social knowledge in determining the network structure and, ultimately, the level of cooperation.

Using web-based experiments, we aim to identify the role of reputational and social knowledge in the emergence of cooperation and the structural features of the network associated with cooperative activity. The general set-up is a group of subjects playing several rounds of a prisoner’s dilemma game on a network, with each round consisting of a network formation stage followed by the game played on the resulting network. The treatments differ in terms of reputational and social knowledge (7, 10). In our baseline treatment, subjects only know who their neighbors are and what the neighbors’ previous actions were. Two further treatments build on the baseline by adding reputational and social knowledge about everyone respectively, allowing a separate investigation of the two channels. A final treatment has reputational and social knowledge about everyone, allowing an exploration of their combined effect on cooperation and the network structure.

**Experimental Setup**

We recruited 364 US-based subjects using the online labor market Amazon Mechanical Turk (AMT), which provides a more diverse subject pool compared with the typical student samples used in laboratory studies (22, 23). Each subject is assigned to a group of 13 and participates in the experiment only once. Unlike some other studies that use subjects from AMT (9, 24, 25), we emulate the workflow and procedures of lab-based experiments by requiring subjects to read the instructions and complete the experiment in a single uninterrupted session, and by preventing multiple participation even by subjects who have only seen the instructions (see SI Appendix for details), which is unusual in laboratory designs.

An experimental session consists of 13–16 rounds of a multiplayer prisoner’s dilemma game on an endogenous network. The first round starts with the empty network with no link between subjects. After round 13, there is a 50% probability that the game terminates in each of the following rounds. Each round consists of three stages. The first two stages determine the network on which subjects play the game. In stage 1, subjects can propose costless links to any of the other subjects and can unilaterally remove any of their existing links. There is no limit to the number of links each subject can remove or propose. If two subjects both propose a link to each other, or if a subject removes a link, then the link is added or removed, respectively. If a subject has proposed a link to another subject who has not done the same, then in stage 2 the recipient of the proposal can accept or reject the proposal. At the end of stage 2, the network is updated with all of the linking decisions.

In stage 3, subjects play a prisoner’s dilemma game by choosing a cooperate (C) or defect (D) action that applies to all their neighbors. The game is completely symmetric in payoffs: (C,C) gives 5 points to each subject, (D,D) gives −3 points, (C,D) gives 3 points to the defector and −5 points to the cooperator, and both subjects get 0 points if they are not linked. The symmetry of the payoff structure leads to intuitive welfare implications: a society of social isolates has welfare 0, and changes to welfare are the payoff structure leads to intuitive welfare implications: a so-

The choice of payoffs and the payment method in our experimental design provides the correct incentive structure to allow the formation of meaningful and realistic network structures, and consequently the isolation of which network features are generated by global reputational and global social knowledge, respectively. The symmetry of payoffs in the gains/losses domains means that both the absence of a connection and connections between a defector and a cooperator lead to no change in social surplus. The only way to produce social surplus is a connection between two cooperators, and, conversely, the only way to reduce social surplus by an equal amount is a connection between two defectors. This is in contrast to other studies that have nonnegative (10) or small negative (8, 9) payoffs, which lead to the emergence of overconnected networks because the losses from being connected to a defector are nonexistent or negligible. Moreover, the random selection of pairs for payment, independent of whether a connection exists or not, ensures that there are uniform incentives throughout the experiment in forming connections, so the payment system does not introduce biases in the emerging network structure. For instance, if we had chosen unconnected pairs from the random selection for payment, then subjects would have incentives to form just one (or very few) link(s) with a cooperator to ensure a specific pairing is picked. This choice is in contrast to previous studies that pay the cumulative number of points subjects have earned (8, 10), which may lead to satisficing in the latest rounds, and therefore lower incentives to change the network.

We conduct four treatments to examine the relative importance of reputational and social knowledge. In the baseline (B) treatment, subjects only have access to local reputational knowledge: a list of their current neighbors with the last five actions chosen by each one of them and a list of the nonneighbors without any information on their past actions. They also have access to local social knowledge only, so they have no information on the structure of the network beyond their neighbors. In the reputation (R) treatment, they have access to global reputational knowledge, so they see a list of the last five actions for every other subject, but they are still limited to local social knowledge. In the network (N) treatment, they have access to global social knowledge, so they see a network figure that shows the connections among all of the subjects in the group, but they only have access to local reputational knowledge. Finally, in the reputation and network (RN) treatment, they have access to global reputational and social knowledge by seeing the whole network and the last five actions for all other subjects. The network figure is interactive, allowing subjects to hover over a node to highlight its neighbors and to drag nodes around to rearrange the network visualization.

**Results**

We begin by investigating how the cooperation level, payoffs, and structure of the network vary at the aggregate level across treatments. In the statistical analysis, we aggregate the data at the session level (n = 7 for each treatment) and apply the non-parametric Kruskal-Wallis test to compare across multiple groups to detect treatment effects, followed by the Dunn’s test with Benjamini-Hochberg adjustment for multiple comparisons
to explore differences between any two treatments. The choice of a nonparametric test and the application of a correction for multiple comparisons with a small \( n = 7 \) sample per treatment after aggregation is very conservative, and therefore any statistically significant finding denotes a sizable treatment effect. The aggregate analysis focuses on rounds 6–13, when information about the previous five actions is available. In this section, KW-D refers to the combination of these tests, and we report adjusted \( P \) values for the Dunn’s test (the Kruskal-Wallis is always significant; see SI Appendix for all of the details and \( P \) values, including a separate analysis of the interaction effect between the treatment variables).

Fig. 1A shows the evolution of the level of cooperation: the availability of global reputational knowledge is the main determinant for the emergence and sustenance of a high level of cooperation. Subjects in the RN treatment achieve an average cooperation level that is larger than in the B (KW-D, \( P = 0.036 \)) and N (KW-D, \( P = 0.060 \)) settings. Likewise, the cooperation level in the R treatment is higher than the B (KW-D, \( P = 0.032 \)) and N (KW-D, \( P = 0.036 \)) settings. There is no significant difference in cooperation level between the RN and R treatments, and between the N and B ones. The evolution of the payoffs subjects receive follows closely the evolution of the level of cooperation. Fig. 1B shows that a consequence of the observed differences in cooperation is that the global reputational knowledge and treatments achieve average payoffs that are approximately twice as large as those of subjects in the B and N settings (KW-D: RN vs. B, \( P = 0.041 \); RN vs. N, \( P = 0.032 \); R vs. B, \( P = 0.031 \); R vs. N, \( P = 0.063 \)).

The differences in cooperation and payoffs across treatments are mainly driven by the dynamics, rather than the initial play in the first round, as there is no significant difference at the 5% level in first-round cooperation or payoffs between any of the treatments. However, treatments R and RN begin with qualitatively higher cooperation levels, and the effect is significant at the 10% level for B compared with treatments B and N (KW-D: R vs. B, \( P = 0.084 \); R vs. N, \( P = 0.050 \)). As a result, subjects earn a marginally higher average payoff in the first round in R and RN compared with B and N, and the effect is significant at the 10% level for R (KW-D, R vs. B, \( P = 0.058 \); R vs. N, \( P = 0.088 \)). A potential explanation is that subjects are more cooperative in the first round because they are aware that their actions will be common knowledge to the group, and this effect is slightly more pronounced in the R treatment because the lack of global network information makes the presence of reputational information more salient. This is consistent with previous findings that contributions in a public good game are higher if subjects are aware that their decisions will affect their reputation in a subsequent indirect reciprocity game (26).

High cooperativeness is associated with the emergence of specific structural properties of the network. Fig. 1C shows the evolution of the density of the network, which is the ratio of the connections in the realized network to the number of connections in the complete network, where all subjects are connected with each other. All treatments start with the same, very high level of density. However, after a few rounds there is a clear differentiation between treatments R and RN with global reputation, where the network remains dense, and treatments B and N with local reputation, where the network becomes sparser (KW-D: RN vs. B, \( P = 0.017 \); RN vs. N, \( P = 0.028 \); R vs. B, \( P = 0.012 \); R vs. N, \( P = 0.014 \)). Fig. 1D shows the evolution of the clustering level of the network, which captures the extent to which a subject’s connections are connected to each other. Similar to the evolution of density, the networks that form in the first round display the same high level of clustering, and the presence of global reputational knowledge leads to the emergence of highly clustered networks (KW-D: RN vs. B, \( P = 0.017 \); RN vs. N, \( P = 0.022 \); R vs. B, \( P = 0.030 \); R vs. N, \( P = 0.048 \)).

We can gain additional insight on the relation between cooperation and network structure by conducting an individual-level analysis to investigate how the association between the position of an individual in the network and the individual’s cooperativeness depends on the availability of reputational and social knowledge. For each treatment, we conduct a logit panel estimation with SEs clustered at the session level, where the dependent variable is the action taken by subjects. We focus on several covariates that capture an individual’s position in the network structure, and we include a large number of controls (see SI Appendix for details).

In the baseline treatment B, no network metric is a significant correlate of cooperativeness, suggesting that the formation of a social structure associated with cooperativeness is not possible when subjects only know the identity and the previous actions of their neighbors. However, network metrics become significant once we add global reputational and global social knowledge independently in the R and N treatments, respectively, and these differ depending on the treatment, which suggests that each type of knowledge plays a different role in the network formation process.

The availability of global reputational knowledge is necessary for the emergence of cooperative hubs: in the R and RN treatments, the number of connections (Degree) of an individual is a highly significant (R: coefficient = 13.38; RN: coefficient = 36.80; \( P < 0.001 \) for both) positive correlate of cooperative behavior, whereas the correlation is insignificant in the B and N treatments, in which only local reputation about the neighbors is available. In other words, cooperators thrive and amass more connections when reputational knowledge about others is available, increasing in this way the density of the overall network. When global reputational knowledge is available, the other significant negative correlate of cooperativeness is Betweenness (27): individuals who connect otherwise separate parts of the network tend to be defectors in both the R (coefficient = −10.85; \( P < 0.001 \)) and RN (coefficient = −19.61; \( P < 0.001 \)) treatments, but the correlation is again insignificant in the N and B treatments.

The addition of global social knowledge to the baseline leads to a significant positive correlation (coefficient = 1.21; \( P < 0.05 \)) between the level of clustering and cooperativeness in the N treatment. This is because the probability that a subject proposes a link to another subject in the N treatment is increasing in the number of neighbors they have in common (coefficient = 0.18; \( P < 0.001 \)), but this relation is insignificant in any of the other treatments (see SI Appendix for details). Interestingly, in the R treatment, where global reputational knowledge is available but global social knowledge is absent, clustering is negatively associated with
cooperativeness (coefficient = -2.08; P < 0.05). In the RN treatment, the two effects cancel out, and clustering is not correlated with cooperativeness.

In summary, our analysis so far shows that the availability of global reputational knowledge increases the level of cooperation, payoffs, and the density and clustering level of the network, whereas global social knowledge does not have an effect on these aggregate metrics. However, mouse movement tracking data reveal that subjects make active use of the network information. The information about the network is displayed using an interactive figure that allows subjects to highlight the neighbors of a node by mouse hovering and to rearrange the network layout by dragging nodes around. On average, subjects hover over 4.3 (SD = 1.5) and 4.9 (SD = 1.3) nodes in each round of the RN and N treatments, respectively. Moreover, subjects drag a node to rearrange the network 10.5% of the times they hover over it in the N treatment and 11.8% of the times in the RN treatment (see SI Appendix for details). For what purpose are subjects using the interactive figure, and does it have any effect on outcomes?

As we have seen, in the N treatment, subjects use the network information in the network formation process: the probability that a subject proposes a link to another subject is increasing in the number of neighbors they have in common. The aggregate data analysis may hide the more subtle role played by global social knowledge in the network formation process, so we further explore its role by conducting an analysis of the communities that emerge in the evolution of the network. We use the well-known Louvain (28) algorithm to detect communities within the network (see SI Appendix for details).

We rank the communities according to their size and focus on the largest (C1) and second largest (C2) ones after they have reached a stable composition. The most frequent outcome of the algorithm is the decomposition of the network into two communities, and C1 and C2 together make up, on average, 85% of the group for all treatments. C1 has an average size of 8.0 and 8.1 subjects in treatments R and RN, respectively, and an average size of 6.6 and 6.8 subjects in B and N, respectively. The size of C2 is about five subjects, on average. There is no significant difference in the size of C1 or C2 across treatments. In the statistical analysis, we aggregate the data at the session level and explore within-treatment differences between C1 and C2 by using the nonparametric Mann–Whitney test (M-W hereafter). A stability analysis reveals that the composition of the communities becomes more stable after round 5, which further corroborates the choice to conduct the analyses by aggregating the data from round 6 onward (see SI Appendix for details).

An analysis of the dynamics of link formation within treatment at the community level reveals that the presence of both global reputational and global social knowledge creates a differentiation in the behavior of subjects in C1 compared with that of subjects in C2. Fig. 2 shows that in the RN treatment subjects in C1 remove more connections on average than subjects in C2: the difference between the average number of connections removed by a member of C1 and by a member of C2 is significant in RN (M-W, P = 0.018), but it is insignificant in any of the other treatments. The mirror image of this metric is the number of links that are removed by others, and the results are consistent: RN is again the only treatment in which there is a significant difference between C1 and C2 (M-W, P = 0.002), and as we would expect, it is members of the C2 community that have more links removed than members of the C1 community (Fig. 2B).

The removal of connections by members of C1 is only effective if the subjects who are outside (or have been expelled) are unable to rejoin the C1 community. Fig. 2C shows that this is indeed the case: the difference between the average number of link proposals rejected by a member of C1 and those rejected by a member of C2 is significant in RN (M-W, P = 0.018), but it is insignificant in any of the other treatments. This shows that there are differences in the network formation process between members of C1 and C2 that are only present when both global reputational and global social knowledge are available, but do these differences have an effect on outcomes?

The addition of global social knowledge to global reputational knowledge has an effect on the distribution of cooperative activity in the group. Fig. 3A shows the difference in the cooperation level between communities C1 and C2 for each treatment. In the RN treatment, community C1 has a 37% higher level of cooperation than community C2 (M-W, P = 0.025), whereas in all other treatments there is no significant difference between the level of cooperative activity in C1 and C2. In other words, the availability of both global reputational and social knowledge allows cooperators to form their own community by actively removing links from defectors and refusing to link with them again, and therefore relegating them to the C2 community. When either global reputational or global social knowledge is unavailable, this process does not occur and cooperators are evenly distributed between the two communities.

The regression analysis at the individual level confirms that the presence of both global reputational and global social knowledge leads to an uneven distribution of cooperative activity in the group. In all of the regressions, we include a Community dummy that is equal to 1 if the individual belongs to C1 and equal to 0 if the individual does not belong to C1. In the RN treatment, there is a positive and significant association between the Community dummy and the level of cooperation (coefficient = 2.02; P = 0.01), whereas there is no significant association for any other treatment. In other words, cooperators congregate in the same community when both global reputational and social knowledge are available, while they are spread out across different communities otherwise.

When both global reputational and global social knowledge are present, members of C1 generate, on average, more surplus from each interaction with another member of their own community compared with members of C2. Fig. 3B shows the difference between the average payoff generated by an interaction with a neighbor within community C1 and by an interaction with a neighbor within community C2 for each treatment, which we can interpret as a measure of how much surplus a community generates. In the RN treatment, each interaction in the C1 community generates, on average, 0.74 additional payoff points than an interaction in the C2 community (M-W, P = 0.018),
whereas the difference is insignificant for any of the other treatments. This effect is sizable: a member of C1 in RN has, on average, 6.4 links with other members of C1, so if the subject was instead a member of C2, and had the same number of links with C2 members, then the potential loss in payoff would be 4.7 points per round, or approximately 23% of the average payoff per round in RN.

Discussion

The point of departure of this study was recent experimental literature showing that the possibility for subjects to choose their partners by forming and breaking connections leads to the emergence of cooperation in the prisoner’s dilemma game. In these studies, reputational knowledge was kept fixed, so subjects knew either only the previous actions of their neighbors (8) or the previous actions of everyone in the group (7, 9, 10). Moreover, subjects only had access to local social knowledge, and thus had no information about the structure of the network with the exception of their neighbors. Our contributions are to show that the extent of reputational knowledge and the extent of social knowledge play crucial and different roles for the emergence and distribution of cooperation, as well as the network features associated with cooperative activity.

Our first contribution is to show that the presence of global reputational knowledge is crucial for the emergence and sustenance of a high level of cooperation. This highlights that the main driver of the results in previous experiments (7, 9, 10) was the implicit assumption of the availability of global reputational knowledge. The treatments in which subjects have access to the previous five actions of everyone in the group achieve a significantly higher level of cooperation than the treatments in which they only have access to the neighbors’ previous five actions. These findings are in agreement with a recent, similar experiment (29) that shows that reputation fosters cooperation by varying the number of past actions available to subjects. The results show the crucial role of global reputational knowledge in determining the emergence of cooperative hubs: individuals who have a high number of connections because they are highly cooperative.

Our second contribution is to show that the availability of global social knowledge on its own affects the process of network formation but has no effect on the overall level of cooperation, payoff, and aggregate network metrics. Specifically, we show that the availability of global social knowledge is associated with a subject’s tendency to propose connections to other subjects who are already connected to her neighbors, which leads to a positive correlation between the individual’s clustering coefficient and her cooperativeness. Previous theoretical work (18, 19) has highlighted the importance of social knowledge in the process of network formation, and our study shows the first evidence to our knowledge of its influence in the network formation process. Moreover, the role of social knowledge in games on networks has so far been almost completely unexplored experimentally, with the exception of a recent experiment showing that social knowledge matters in public good games on networks (21). The systematic experimental study of the role of social knowledge in network formation and in game play across different types of games is a promising area of future studies.

Our third contribution is to show that the availability of both global reputational and global social knowledge has an effect on the distribution of cooperative activity in the group. The presence of both types of knowledge allows cooperators to remove links from defectors and reject their link proposals in future rounds. In this way, cooperators are able to form a community that is more cooperative than the community of defectors, and it generates a larger social surplus from within community interactions. An open question for future research is the scalability and robustness of these findings to the overall size of the group. It is reasonable to imagine that the complexity of processing information about the network grows exponentially with the size of the network, making it more challenging to use it in the process of network formation. However, at the same time, the benefits from belonging to the cooperative community grow with the size of the community, making the emergence of large cooperative communities more attractive in a larger group.

The finding that global reputational information is crucial for the emergence of a high level of cooperation is consistent with previous “theoretical and empirical studies of indirect reciprocity [that] stress the importance of monitoring not only partners in continuing interactions but also all individuals within the social network” (30) and with the finding that cooperation is higher in connected networks within which everyone is monitored (31). As predicted by theory (32, 33), experimental studies on indirect reciprocity with well-mixed populations show that reputation is important for cooperation (14, 34) and that cooperation increases with the richness of the reputation information (35), as well as the punishment/reward technology (36) available. In this study, we find that, in the context of dynamic networks, cooperation almost doubles if reputation is available about everyone, rather than just one’s connections.

The experimental result that the presence of global reputational knowledge is essential for the emergence of a high level of cooperation contributes to a growing and fruitful two-way dialogue between the theoretical and experimental literatures on cooperation in networks. Our results indicate that access to this additional social knowledge (19) shows the first evidence to our knowledge of its influence in the network formation process. Moreover, the role of social knowledge in games on networks has so far been almost completely unexplored experimentally, with the exception of a recent experiment showing that social knowledge matters in public good games on networks (21). The systematic experimental study of the role of social knowledge in network formation and in game play across different types of games is a promising area of future studies.
reputational knowledge allows the emergence of a community of cooperators. Exploring whether this type of effect of social knowledge extends to other domains is an important direction for future inquiries.

Materials and Methods

We recruited US-based subjects on AMT, using a simple qualification task and a sociodemographic survey to obtain their AMT ID information. We invited participants in a session by completing the following steps: Waiting Room; Instructions and Interface Tour; Quiz; Game; Final Questionnaire; and Payment Confirmation. We paid subjects using AMT within 30 minutes after the session: we used 28 sessions (seven sessions per treatment, 364 subjects in total) because two sessions experienced dropped out subjects after the game started and were excluded from our main analysis. The average earnings per subject were $5.13, including a $2 fixed fee for participation (55). Subjects remained completely anonymous throughout the qualification task and the experiment. Repeated and multiple participation were prevented by logging subjects’ AMT IDs and their IP addresses. See the SI Appendix for further details about the experiment. This research was approved by the Cambridge Experimental and Behavioral Economics Group on the use of human subjects, and informed consent was obtained from subjects before participation.

ACKNOWLEDGMENTS. We thank Angel Sanchez for his comments and for sharing his results before publication. We also thank Syngjoo Choi, Vessella Daskalova, Neli Demireva, Sanjeev Goyal, Margaret Meyer, Chris Smith, and Adam Szedl for their suggestions. Generous research support from the Keynes Fund for Applied Economics in Cambridge (E.G.; project title: “Social Network Structure and Economic Outcomes: An Investigation Using Online Experiments”), Balliol Interdisciplinary Institute (C.Y.), and Oxford-Man Institute of Quantitative Finance (C.Y.) is thankfully acknowledged.

Supporting Information

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1 Experimental Details

We conducted all our experimental sessions using subjects recruited from Amazon Mechanical Turk (AMT), a popular online labor market. Workers (called Turkers) at AMT complete short tasks (called Human Intelligence Tasks or HITs) in return for monetary compensation. AMT hosts a large and diverse population of Turkers, which provides researchers with on-demand access to its labor [1, 2, 3]. AMT enables researchers to conduct research with significantly larger and more diverse subject pools compared to the typical laboratory experiments.

In our experiment, all the subjects are U.S-based and we enforce this requirement by restricting our HITs to U.S. Turkers as well as checking their IP addresses upon participation. All collected data are associated with subjects’ Turker IDs only, and not with any personally identifiable information.

There are considerable differences in recruitment and experimental procedures among the few published studies that involve real-time interaction between subjects from AMT. In particu-
lar, some previous studies [4, 5, 6] allow subjects to participate in multiple sessions in the same experiment: subjects are allowed to participate in the same treatment multiple times and/or in different treatments. In addition, their main analysis is based on data collected in later sessions only. In contrast, our experiment actively prevents multiple/repeated participation even in cases where the subject only saw the Instructions and then abandoned the experiment. Analogous to other contributions [7, 8], our study requires subjects to read the Instructions and complete the experimental Game in a single uninterrupted session, emulating the workflow of lab experiments.

More specifically, participation in our experiment consists of two parts. First, subjects have to pass a Qualification HIT in which we collect demographic information, and ask basic comprehension questions about the Janken Step game, which is a simple variant of the popular rock, paper and scissors game. The comprehension questions serve the purpose of filtering out a small minority of subjects who are extremely careless in reading and/or have difficulties in understanding the simple Janken Step game and its payoff matrix. We believe that this filtering leads to a negligible bias in our subject pool, because the chosen game is so simple and common that it merely requires rudimentary reading and arithmetic skills (i.e. addition of single-digit numbers) and the failure rate is only 6.6%. Second, we randomly invite qualified subjects by email using AMT’s ID-based notification system. Invitations were sent individually so that subjects did not know who else was invited in the same session. In our invitation email, we specify the time and date of the experiment and do not disclose any details of the experimental design. To participate in the actual experiment, subjects need to locate and accept the HIT, and click on a URL to access an external web page hosted on UbiquityLab, our purpose-built platform for online experimentation. The experiment consists of the following steps: Waiting Room; Instructions and Interface Tour; Quiz; Game; Final Questionnaire; and Payment Confirmation. At the end of the experiment subjects need to copy a unique confirmation code and
submit it on the AMT HIT page for payment.

The graphical game interface requires mouse inputs only, and provides various information to subjects depending on the current stage of the game and the treatment.

In the first stage, subjects see their own previous five actions, their current neighbors’ previous five actions, and, in treatments $R$ and $RN$ only, their non-neighbors’ previous five actions. In all treatments, there is a figure that shows the subject’s current neighbors. In the $N$ and $RN$ treatments, there is also an interactive figure (see Figure S1) that displays the current network in the group: subjects can highlight any node and its neighbor(s) by hovering the mouse pointer onto the node, and they can also rearrange the network layout by dragging the nodes around as the link(s) will automatically adapt to the changes. In the $B$ and $R$ treatments, the network figure is replaced by a figure of all the non-neighbors.

![Interactive network figure](image)

**Figure S1:** Interactive network figure of the connections among all the subjects in the $RN$ treatment.

In the second stage, subjects see the same reputational and network information as in the first stage. Additionally, they receive notification(s) of link proposals from any non-neighbor
who has chosen to propose a connection in the first stage, and have to decide whether to accept or reject each proposal. In treatments with network information, they can continue interacting with the network figure while making their decisions.

In the third stage, both network and reputational information are updated to reflect the outcomes of the link formation/removal choices and the rejection/acceptance of proposal(s) in stages 1 and 2 respectively. Subjects observe the updated information about their neighbors. In treatments $B$ and $N$, subjects can see the reputational information of their new neighbors, and cannot access any longer the reputational information of removed neighbors. Based on the updated network and reputational information available in each treatment, each subject chooses to cooperate or defect.

The beginning of the experiment starts with the empty network where no subject is connected to any other, and there is no reputational information. In round $x \in \{1, 16\}$ subjects can see the last $\min\{x - 1, 5\}$ actions played by their neighbors (in $B$ and $N$) or everyone in the network (in $R$ and $RN$). In other words, before round 5 subjects can see the actions up to that round, and after round 5 they see the actions of the previous 5 rounds.

Visually, the interface is organized into three main panels, as shown in Figure S2. The top left panel shows the graphical representation of the subject’s current neighbors, with the subject herself at the center. The bottom left panel shows the graphical representation of either all other unlinked subjects (in $B$ and $N$) or all the subjects including the subject herself (in $R$ and $RN$). In $R$ and $RN$, the network is laid out using a customized force-based layout algorithm [9] that we fine-tune specifically for networks of 13 individuals. In each stage, the network layout is exactly the same for all subjects in a session except for the labeling of the “You” node that denotes the position of the subject herself. We performed extensive testing to ensure that the algorithm effectively captures and visualizes important structural features such as symmetries and regularities in the network.
Figure S2: Three-panel design of the game interface. The screenshot shown here is stage 1 of a round in the $RN$ treatment.

The right panel contains four blocks from top to bottom:

The first block indicates the current stage and current round of the game, and the time left for making an input. In the first stage, subjects have 70 seconds to propose and cut links. In the second stage, subjects have 45 seconds to accept or reject any link proposal(s) they may have received. In the third stage, subjects have 25 seconds to choose an action. At the end of a round, subjects have 10 seconds to view the results.

The second block reminds the subject of her own past actions. The “Table of Points” link on the right allows the subject to see the payoff information of the game by hovering her mouse pointer on the link.
Figure S3: In stage 1 the third block in the right panel displays other subjects’ previous actions and allows subjects to propose and cut links. The example screenshot above is what a subject would see in treatments $R$ and $RN$ with global reputational information. A green box with an “A” indicates that the subject has chosen to cooperate, a blue box with a “B” indicates that the subject has chosen to defect, and a gray box denotes that the subject has not taken an action. For instance, in the screenshot above we have that in the previous round subject $H$ chose to defect and $N$ chose to cooperate. Notice that if a subject does not take an action then the computer selects the defect action by default.

In the first stage, the third block lists the neighbors (on the left) and non-neighbors (on the right) that are carried over from the last round, and their respective actions in the previous five rounds. In the $B$ and $N$ treatments with local reputational information, subjects can only see the history of actions of their neighbors. Subjects are free to propose and cut any link by ticking the box next to the fictitious initial of any other subject (see Figure S3). In the second stage, any unmatched link proposal is shown in the non-neighbors list: a “Y/N” button appears next to the non-neighbor who sent the proposal, and the subject then needs to choose ‘Y’ (for Yes) or ‘N’ (for No) for each proposal (see Figure S4). In the third stage, both neighbors and non-neighbors lists are updated based on the results of the earlier stages.
Figure S4: In stage 2 the third block in the right panel displays the reputational information of other subjects and allows subjects to approve or reject other subjects’ link proposals.

The bottom block indicates what the subject needs to do in each stage and shows the button(s) for making an input. In the first two stages, it displays a “Submit” button the subject can use to confirm her choices. In the third stage, it displays the choices between the “A” (denoting cooperate) and “B” (denoting defect) buttons, and a separate “Submit” button for confirming the choice (see Figure S5).

Figure S5: In stage 3 the bottom block allows subjects to choose between “A” (cooperate) and “B” (defect).

The Game lasts for at least 13 rounds and at most 16 rounds. Starting from the 13th round, the game may randomly terminate with a 50% probability, which subjects are informed about.
in the Instructions.

2 Sample Description

The main experimental data contains the decisions of 364 subjects, and multiple participations are not allowed. We ran a total of 30 sessions starting at 11am EST between the 12th and the 21st of December, 2013. UbiquityLab allows us to run several sessions concurrently in a single “meta-session”. We ran 9 meta-sessions consisting of 2 to 5 sessions each. In 2 out of 30 sessions subjects dropped out so we excluded them from the main analysis, but the results are unchanged if we include these sessions (see Section 7 for details). A single experimental session lasted on average 49.6 minutes. Subjects were paid a fixed $2 fee and a bonus based on their performance. The average earnings was $5.13. These earnings are above the average hourly earnings for a Turker on AMT.

There are 13 subjects in each session, and the choice of this sample size stems from a number of considerations. First, the exploration of the impact of social knowledge required networks with a large enough number of subjects to make the task of processing network information non-trivial. Conversely, we did not want the number of subjects to be very large in order to avoid making the network information too complex to be usable by subjects. Second, from the operational side of the experiment, we wanted to minimize the possibility of subjects dropping out of the experiment, and this probability is clearly increasing in the size of the sessions. Finally, we did not want to depart significantly from the session sizes used by previous contributions to the investigation of cooperation in dynamic networks [5, 7, 8, 10]. The choice of 13 subjects per session turned out to be the best option given these considerations.

We match the experimental data with the Questionnaire data. Table S1 summarizes the main socio-demographic characteristics of the participants and their pairwise correlations. All the participants are residents in the U.S.: 43% are female and the average age is 32.6 years
old. We asked subjects the standard interpersonal trust question from the World Values Survey (WVS) and found that about 52% believe that others can be trusted, which is higher than the average value from the WVS survey of the U.S. population. The level of trust is not correlated with gender, age or education.

Table S1: Summary statistics and pairwise correlations for the main variables.

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean</th>
<th>s.d.</th>
<th>Gender</th>
<th>Age</th>
<th>Education</th>
<th>Trust</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender(^1)</td>
<td>364</td>
<td>0.43</td>
<td>0.50</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>364</td>
<td>32.63</td>
<td>10.33</td>
<td>0.06</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education(^2)</td>
<td>364</td>
<td>3.35</td>
<td>1.35</td>
<td>-0.00</td>
<td>0.11*</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust(^3)</td>
<td>364</td>
<td>0.52</td>
<td>0.50</td>
<td>-0.05</td>
<td>0.09</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HL(^4)</td>
<td>333</td>
<td>7.54</td>
<td>1.74</td>
<td>-0.00</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.02</td>
<td>1.00</td>
</tr>
</tbody>
</table>

\(^* P < 0.05. \) 1. Female = 1. 2. See the caption of Figure S6(b) for codings; 3. Trust question with 0 = “Need to be very careful” and 1 = “Most people can be trusted”; 4. Holt and Laury’s risk attitude test: 21 participants are excluded because they made at least one inconsistent choice (i.e. multiple switching points) and 10 participants are excluded because they had no switching point.

Figure S6 illustrates in more detail the composition of the subject pool, which is more representative of the general population than the student populations that are typical of most laboratory studies. Figure S6(a) shows that subjects belong to different age groups ranging from a minimum of 18 to a maximum of 70 years old. There is also a significant heterogeneity in the education level of participants. Figure S6(b) shows that 6.9% of participants only have a high school diploma, 76.9% have attained some kind of college education, and 15.9% have a master, professional degree or Ph.D. As one would expect, there is a significant positive correlation between age and education level.

During the Questionnaire, subjects also took the Holt and Laury’s risk attitude test [11]: there are 10 scenarios and in each scenario a subject has to pick between a safe and a risky
lottery. In the early scenarios the safe lottery gives a higher expected payment, while in the late scenarios it is the opposite. A risk-neutral participant would switch from the safe to the risky lottery at scenario 5. The mean switching point is 7.5 so the participants are on average risk-averse. There are 10 (3%) participants who switched at or before scenario 4 and therefore are risk-seeking, and 40 (12%) participants who are risk-neutral. There is no significant correlation of risk aversion with gender, age, education or trust.

3 Further Experimental Data

In this section we report additional data on subjects’ decisions during the experiment.

On average, subjects take 18.9 minutes ($SD = 3.4$) to complete the Instructions and the Quiz. There are slight variations in the Instructions and the Quiz across treatments, so the average time spent on them are 18.1, 20.4, 17.1 and 20.0 minutes for treatments $B$, $N$, $R$ and $RN$ respectively.

In the Quiz there are 5 questions in the $B$ and the $R$ treatments, and 6 questions in the $N$ and the $RN$ treatments. The extra question in the $N$ and $RN$ treatments tests subjects’ under-
standing of the interactive features of the network figure in the interface, which are available only in those two treatments. Subjects have a maximum of 3 tries to pass the Quiz, and in case they fail the third try they are not allowed to continue to the experiment. Moreover, after each unsuccessful attempt, we randomly re-generate the numbers in the failed question(s) for the subsequent try to ensure it is very unlikely that subjects pass the Quiz by randomly guessing the answer through trial and error. Overall, subjects take on average 1.5 \( (SD = 0.7) \) tries to answer correctly all the questions. The mean numbers of tries for treatments \( B, N, R \) and \( RN \) are 1.5, 1.6, 1.4 and 1.5 respectively, and there is no significant difference across treatments. 64.0% of subjects pass the Quiz in their first try, 24.7% pass with two tries, and 11.3% need three tries. For those subjects who do not pass the Quiz in their first try, they make on average 1.4 \( (SD = 0.6) \) mistakes in their first try and 1.3 \( (SD = 0.5) \) mistakes in their subsequent try (if required).

On average, subjects spend 20.9 \( (SD = 3.6) \) minutes to play the experimental game. The mean time for subjects to submit their choices in the first stage is 16.3 \( (SD = 8.2) \) seconds, the mean time in the second stage is 11.3 \( (SD = 6.8) \) seconds, and the mean time in the third stage is 9.1 \( (SD = 4.0) \) seconds. During the \( N \) and \( RN \) treatments, we implement real-time tracking of subjects’ mouse movements on the network figure of the interface, in terms of both the number of times a subject hovers over a node with the mouse pointer to highlight that node and its neighbors, and the number of times a subject clicks and drags the nodes to re-arrange the network layout. Figure S7 below shows the evolution of both measurements over the course of the game for both the \( N \) and \( RN \) treatments. On average, subjects hover over 4.3 \( (SD = 1.5) \) and 4.9 \( (SD = 1.3) \) nodes in each round of the \( RN \) and \( N \) treatments respectively. Every instance of node dragging is also recorded as an instance of hovering over a node, so we measure the usage of node dragging per round in terms of the percentage of times that hovering over a node involved node dragging as well, as shown by the red line in Figure S7. Subjects
drag a node to re-arrange the network 10.5% of times they hover over it in the $N$ treatment, and 11.8% of times in the $RN$ treatment. The relatively lower usage of the node dragging feature may indicate that our customized force layout algorithm is effective at displaying the network and subjects do not need to re-arrange its layout manually.

Figure S7: Usage of the interactive features of the network figure in treatments (a) $N$ and (b) $RN$. The blue line shows the evolution of the usage of hovering over a node during the game, while the red line shows the evolution of the usage of node dragging (as a percentage of instances of hovering over a node).

4 Louvain community detection algorithm

We use the Louvain community detection algorithm [12] to detect communities in the network structure that emerges in each round. The Louvain method adopts a hierarchical design to greedily partition the network into communities that obtain the highest value of modularity. Modularity is defined as:

$$Q = \frac{1}{2L} \sum_C \left( 2l_C - \frac{d_C^2}{2L} \right)$$

where $L$ is the total number of links in the network, $C$ denotes a community, $l_C$ is the number of links in community $C$, $d_C = \sum_{i \in C} d_i$ is the sum of the number of connections, or degree, $d_i$ for each subject $i \in C$. The algorithm starts by placing each node in its own community and
seeks to merge it with neighboring communities such that the modularity gain is maximized by iterating through every node. A node that is previously merged to a community can be detached to join a new community in subsequent iterations, which allows the algorithm to correct initial sub-optimal choices. This phase is repeated until it is not possible to move a node to achieve an increase in modularity. The second phase builds a new network by collapsing all the nodes of the same community into a “super node”, and then it runs the first phase with this new network consisting of super nodes. This alternating two-phase procedure is repeated several times until there is no more improvement in modularity. The pseudo-code in Algorithm S1 summarizes the algorithm.

Algorithm S1 Louvain Community Detection Method

Require: $G$ the original network

1: loop
2: Initialize each node of $G$ as a cluster
3: while some node(s) can be moved do
4: for every node $i$ in $G$ do
5: Move $i$ to a neighboring community to maximize the modularity gain if possible, otherwise retain $i$ in its own community
6: end for
7: end while
8: if resulting modularity is higher than before then
9: Collapse each cluster into a super node
10: $G \leftarrow$ the network of super nodes
11: else
12: return resulting clusters and terminate
13: end if
14: end loop

Using the Louvain method, we detect communities that emerge in each round of the experimental game and order them by size in descending order. Figure S8(a) shows the distribution of the number of detected communities in each treatment. There is no difference across treatments in terms of the fragmentation of the networks. The most frequent outcome of the algorithm is the decomposition of the network into two communities, followed by the decomposition into three communities. There is no significant difference across treatments in terms of the number of communities that emerge in the networks. Figure S8(b) shows the distribution of the mean sizes of communities for each treatment. We find that communities 1 and 2 together make up
on average over 85% of the group for all the treatments.

Figure S8: (a) Distribution of the number of detected communities in each treatment: the percentages are calculated using $\frac{\text{number of occurrences}}{13 \times 7}$, where 13 is the total number of rounds in each of the 7 sessions in a treatment. (b) Distribution of the mean sizes of communities in each treatment: the labels (e.g. 1, 2, 3, etc) on the x-axis within each treatment denote communities (e.g. $C_1$, $C_2$, $C_3$, etc).

5 Detailed analysis

In this section we describe the technical details and provide further analysis of our data. We have organized it in three separate parts: section 5.1 presents the aggregate analysis at the session level, section 5.2 presents the analysis at the community level, section 5.3 presents the regression analysis at the individual level, and section 5.4 presents a visual summary of our results.

5.1 Aggregate level

After aggregating the data at the session level, we use the Kruskal-Wallis test [13] to detect the presence of a treatment effect by comparing across treatments, and use the Dunn’s test [14] as the post-hoc test to conduct multiple pairwise comparisons between treatments. We choose the Dunn’s test because: (a) it uses the same ranks as those in the Kruskal-Wallis test; and (b) it uses
the pooled variance implied by the null hypothesis in the Kruskal-Wallis test. Other pairwise comparison tests (e.g. the Mann-Whitney test) are not appropriate as the post-hoc test following the Kruskal-Wallis test because they violate (a) and (b). Furthermore, we apply the Benjamini-Hochberg adjustment [15] method with a 5% false discovery rate to the Dunn’s test to control for the false discovery rate during the multiple comparisons. The choice of a non-parametric test and the application of a correction for multiple comparisons with a small $n = 7$ sample per treatment after aggregation is very conservative, and therefore any statistically significant finding denotes a sizable treatment effect.

Table S2 lists the full results of the Kruskal-Wallis tests and the Dunn’s tests with P-values adjusted using the Benjamini-Hochberg correction (with a 5% false discovery rate) for different variables at the aggregate level from round 6 to 13. We report the results for the same range of rounds as in the main text.

Table S3 replicates the analysis in Table S2 for rounds 1 to 13. Note that prior to round 5 subjects have access to all the past actions of their neighbors (in $B$ and $N$) or everyone in the group (in $R$ and $RN$), while after round 5 they have access to the previous 5 actions. The inclusion of these initial rounds in our analysis has no substantial impact on our results.

Table S4 replicates the analysis in Table S2 for round 1 only. The results show that there is no significant difference in subjects’ play in the very first round of the experiments between different treatments.
Table S2: Results of the Kruskal-Wallis tests and the Dunn’s tests with P-values adjusted using the Benjamini-Hochberg correction for different variables at the aggregate level from round 6 to 13. \( n = 7 \) sample size per treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kruskal-Wallis Test ( (\chi^2(3) , P\text{-value}) )</th>
<th>Dunn’s Test ( (z\text{-statistic} , P\text{-value}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coop. Level</td>
<td>( 9.538 , 0.023 )</td>
<td>( RN \quad B \quad N )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.096 , 0.036 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.323 , 0.227 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.060 , 0.492 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.065 , -2.031 , -2.259 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.474 , 0.032 , 0.036 )</td>
</tr>
<tr>
<td>Avg. Payoff</td>
<td>( 9.545 , 0.023 )</td>
<td>( RN \quad B \quad N )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.047 , 0.041 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.307 , 0.260 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.032 , 0.477 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.000 , -2.047 , -2.307 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.500 , 0.031 , 0.063 )</td>
</tr>
<tr>
<td>Density</td>
<td>( 9.538 , 0.006 )</td>
<td>( RN \quad B \quad N )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.535 , 0.017 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.600 , 0.065 )</td>
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<tr>
<td></td>
<td></td>
<td>( 0.028 , 0.474 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.130 , -2.405 , -2.470 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.538 , 0.012 , 0.014 )</td>
</tr>
<tr>
<td>Clustering</td>
<td>( 11.090 , 0.011 )</td>
<td>( RN \quad B \quad N )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 2.762 , 0.017 )</td>
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<tr>
<td></td>
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<td></td>
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<td>( 0.585 , -2.177 , -1.852 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( 0.335 , 0.030 , 0.048 )</td>
</tr>
</tbody>
</table>
Table S3: Results of the Kruskal-Wallis tests and the Dunn’s tests with P-values adjusted using the Benjamini-Hochberg correction for different variables at the aggregate level from round 1 to 13. \( n = 7 \) sample size per treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kruskal-Wallis Test ( (\chi^2(3), P\text{-value}) )</th>
<th>Dunn’s Test ( (^{z}\text{-statistic}, P\text{-value}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coop. Level</td>
<td>9.583, 0.023</td>
<td>( R\text{N} \quad 1.949 \quad B \quad 0.038 \quad N \quad 2.144 \quad 0.195 \quad N \quad 0.032 \quad 0.423 \quad R \quad -0.260 \quad -2.209 \quad -2.404 \quad R \quad 0.477 \quad 0.041 \quad 0.049 )</td>
</tr>
<tr>
<td>Avg. Payoff</td>
<td>9.350, 0.025</td>
<td>( R\text{N} \quad 1.884 \quad B \quad 0.045 \quad N \quad 2.047 \quad 0.162 \quad N \quad 0.041 \quad 0.436 \quad R \quad -0.357 \quad -2.242 \quad -2.404 \quad R \quad 0.433 \quad 0.038 \quad 0.049 )</td>
</tr>
<tr>
<td>Density</td>
<td>10.060, 0.018</td>
<td>( R\text{N} \quad 2.307 \quad B \quad 0.063 \quad N \quad 2.242 \quad -0.065 \quad N \quad 0.038 \quad 0.474 \quad R \quad 0.065 \quad -2.242 \quad -2.177 \quad R \quad 0.569 \quad 0.025 \quad 0.022 )</td>
</tr>
<tr>
<td>Clustering</td>
<td>10.997, 0.012</td>
<td>( R\text{N} \quad 2.502 \quad B \quad 0.037 \quad N \quad 2.339 \quad -0.162 \quad N \quad 0.029 \quad 0.436 \quad R \quad 0.162 \quad -2.339 \quad -2.177 \quad R \quad 0.523 \quad 0.019 \quad 0.022 )</td>
</tr>
</tbody>
</table>
Table S4: Results of the Kruskal-Wallis tests and the Dunn’s tests with P-values adjusted using the Benjamini-Hochberg correction for different variables at the aggregate level for round 1. *n = 7* sample size per treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kruskal-Wallis Test ($\chi^2(3)$, $P$-value)</th>
<th>Dunn’s Test ($z$-statistic, $P$-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coop. Level</td>
<td>6.455 (0.092)</td>
<td>$\begin{array}{lll} RN &amp; B &amp; N \hline 1.123 &amp; 0.261 &amp; 1.058 \ B &amp; 0.174 &amp; 0.474 \ N &amp; -1.074 &amp; -2.197 \ R &amp; 0.212 &amp; 0.084 \ &amp; &amp; -2.132 &amp; 0.050 \end{array}$</td>
</tr>
<tr>
<td>Avg. Payoff</td>
<td>6.187 (0.103)</td>
<td>$\begin{array}{lll} RN &amp; B &amp; N \hline 1.091 &amp; 0.977 &amp; 0.207 \ B &amp; 0.114 &amp; 0.455 \ N &amp; -1.091 &amp; -2.067 \ R &amp; 0.276 &amp; 0.058 \ &amp; &amp; -2.181 &amp; 0.088 \end{array}$</td>
</tr>
<tr>
<td>Density</td>
<td>2.387 (0.496)</td>
<td>$\begin{array}{lll} RN &amp; B &amp; N \hline 0.000 &amp; 0.000 &amp; 0.016 \ B &amp; 0.500 &amp; 0.952 \ N &amp; 0.016 &amp; 0.740 \ R &amp; -1.256 &amp; -1.256 \ &amp; &amp; -1.272 &amp; 0.610 \end{array}$</td>
</tr>
<tr>
<td>Clustering</td>
<td>3.547 (0.315)</td>
<td>$\begin{array}{lll} RN &amp; B &amp; N \hline 1.219 &amp; 1.219 &amp; 1.137 \ B &amp; 0.223 &amp; 0.192 \ N &amp; -0.081 &amp; 0.468 \ R &amp; -2.76 &amp; -1.495 \ &amp; &amp; -1.414 &amp; 0.236 \end{array}$</td>
</tr>
</tbody>
</table>
We also run Ordered Logistic Regression (with the proportional odds model) for the same variables at the aggregate level, which allows us to test for interaction effects between the (indicator) treatment variables rep and net using effect coding (B: rep = −1, net = −1; N: rep = −1, net = 1; R: rep = 1, net = −1; RN: rep = 1, net = 1). This regression model can be seen as a generalization of the Kruskal-Wallis test, and caters for more than two outcomes in the dependent variable. We apply a rank-transformation before running the OLR, and such transformation induces a natural ordering from the data. Table S5 lists the results of these regressions for the rounds between 6 and 13, and shows that the presence of global reputational knowledge (i.e. indicator variable rep = 1) has a significant effect on the level of cooperation, average payoff per round, density and clustering of the networks, while the presence of global social knowledge (i.e. indicator variable net = 1) and the interaction between global reputational and global social knowledge are not significant at the aggregate level.

As a robustness check for these results, we also run the same analysis using the Robust Regression model. In these regressions we use the original outcome variables, and therefore we do not apply a rank-transformation before running the analysis. Table S6 lists the results of these regressions for the rounds between 6 and 13, and the conclusions are unchanged: global reputational knowledge has a significant effect on the level of cooperation, average payoff per round, density and clustering of the networks, while the presence of global social knowledge and the interaction between global reputational and global social knowledge are not significant at the aggregate level.
Table S5: Treatment effects at aggregate level using ordered logistic regression. \( n = 7 \) sample size per treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th></th>
<th>Coop. Level</th>
<th>Avg. Payoff</th>
<th>Density</th>
<th>Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>rep</td>
<td>1.296**</td>
<td>1.285**</td>
<td>1.745***</td>
<td>1.514***</td>
</tr>
<tr>
<td></td>
<td>(0.408)</td>
<td>(0.406)</td>
<td>(0.483)</td>
<td>(0.459)</td>
</tr>
<tr>
<td>net</td>
<td>-0.201</td>
<td>-0.220</td>
<td>-0.189</td>
<td>0.200</td>
</tr>
<tr>
<td></td>
<td>(0.334)</td>
<td>(0.336)</td>
<td>(0.334)</td>
<td>(0.329)</td>
</tr>
<tr>
<td>rep \times net</td>
<td>0.074</td>
<td>0.078</td>
<td>-0.011</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.334)</td>
<td>(0.336)</td>
<td>(0.335)</td>
<td>(0.329)</td>
</tr>
<tr>
<td>Observations</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td>11.863</td>
<td>11.808</td>
<td>17.393</td>
<td>14.472</td>
</tr>
<tr>
<td>( P &gt; \chi^2 )</td>
<td>0.008</td>
<td>0.008</td>
<td>0.001</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. * \( P < 0.05 \), ** \( P < 0.01 \), *** \( P < 0.001 \).
Table S6: Treatment effects at aggregate level using robust regression. n = 7 sample size per treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th></th>
<th>Coop. Level</th>
<th>Avg. Payoff</th>
<th>Density</th>
<th>Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>rep</td>
<td>0.155**</td>
<td>6.471**</td>
<td>0.120***</td>
<td>0.082***</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(1.622)</td>
<td>(0.027)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>net</td>
<td>-0.021</td>
<td>-0.927</td>
<td>-0.015</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(1.622)</td>
<td>(0.027)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>rep × net</td>
<td>0.004</td>
<td>0.427</td>
<td>-0.005</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(1.622)</td>
<td>(0.027)</td>
<td>(0.020)</td>
</tr>
</tbody>
</table>

Observations 28 28 28 28

$F$ 5.341 5.437 6.566 5.852

$P > F$ 0.006 0.005 0.002 0.004

Standard errors in parentheses. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

5.2 Community level

After aggregating the data at the session level, we use the Mann-Whitney test for pairwise comparisons to detect the presence of within treatment differences between $C_1$ and $C_2$ for each treatment.

Table S7 lists the full results for the Mann-Whitney tests that compare $C_1$ and $C_2$ within treatments for the variables in Figure 2 and Figure 3 of the main text. For each comparison we report the $z$-statistic and the $P$-value.
Table S7: Results of the Mann-Whitney tests for comparing $C_1$ and $C_2$ for different variables at the community level from round 6 to 13. $n = 7$ sample size for each community in each treatment after aggregation at the session level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>B $z$-statistic $P$-value</th>
<th>N $z$-statistic $P$-value</th>
<th>R $z$-statistic $P$-value</th>
<th>RN $z$-statistic $P$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coop. Level</td>
<td>0.192 0.848</td>
<td>-0.319 0.749</td>
<td>0.703 0.482</td>
<td>2.236 0.025</td>
</tr>
<tr>
<td>Comm. Neighbor Payoff</td>
<td>0.640 0.522</td>
<td>-0.192 0.848</td>
<td>0.704 0.482</td>
<td>2.364 0.018</td>
</tr>
<tr>
<td>Links Removed</td>
<td>0.703 0.482</td>
<td>0.447 0.655</td>
<td>0.128 0.898</td>
<td>2.364 0.018</td>
</tr>
<tr>
<td>Removals Received</td>
<td>-0.703 0.482</td>
<td>0.447 0.655</td>
<td>-1.663 0.096</td>
<td>-3.130 0.002</td>
</tr>
<tr>
<td>Proposals Rejected</td>
<td>0.064 0.949</td>
<td>0.064 0.949</td>
<td>-1.597 0.110</td>
<td>-2.364 0.018</td>
</tr>
</tbody>
</table>

Figure S9: Cooperation level (a), density (b), and clustering (c) of the largest and the second largest communities for treatments B, N, R and RN. Error bars indicate ± one SEM. For each treatment data is aggregated for each community at the session level. Figure S9 shows the aggregated absolute levels of cooperation, density and clustering for $C_1$ and $C_2$ in each treatment. As Table S7 above shows, there is a significant difference in cooperation level between $C_1$ and $C_2$ in RN, but not in any of the other treatments. As the
figures suggest, there is a qualitative difference in density and clustering between \( C_1 \) and \( C_2 \) in the \( RN \) treatment, but this difference is not significant for \( RN \) or any of the other treatments.

5.3 Individual level

Table S8 lists the full output of the logit panel estimation with random effects per subject and standard errors clustered at the session level. The dependent variable is the action taken by subjects (1 = cooperate), and we exclude observations (35 out of 5,018 or 0.7% of the total) in which subjects take no action.

We include the following network metrics as independent variables to investigate the association between network structure and cooperation: Degree is the number of connections; Clustering is the local clustering coefficient [16]; Betweenness is the betweenness centrality index [17]; Eigenvector is the eigenvector centrality index [18]; and Community equals to 1 if the individual is part of the largest community \( C_1 \) and equals to 0 if the individual is part of the second largest community \( C_2 \).

Payoff captures the number of points the individual wins in a round. The \( L1.action, L2.action, L3.action, L4.action, \) and \( L5.action \) variables are controls for lagged actions, so \( Lx.action \) denotes the action the individual took \( x \) rounds before. We also include a number of socio-economic characteristics (Gender, Age, Education), a measure of Trust from the standard question from the World Values Survey, and the results of a Holt-Laury risk elicitation test from the Questionnaire, see the caption of Table S1 for details on the coding of the variables.

We have a number of controls for the linking behavior of subjects in a given round. Links added is the number of new links the subject adds in a given round; Total links removed is the number of links the subjects loses (either by removing others or by being removed by others); Proposals received is the number of link proposals received by the subject; Removals received is the number of link removals received by the subject; Proposals approved is the number of a
subject’s link proposals approved by others; and Proposals rejected is the number of a subject’s link proposals rejected by others.

Time 1, Time 2 and Time 3 denote the time in seconds that subjects take to complete stage 1, 2 and 3 respectively in each round. Mouse hover 1, Mouse hover 2 and Mouse hover 3 capture the number of times a subject hovers over a node in the network figure in stages 1, 2 and 3 respectively. Mouse drag 1, Mouse drag 2 and Mouse drag 3 capture the number of times a subject clicks and drags nodes in the network figure in stages 1, 2 and 3 respectively. Quiz tries denotes the number of times a subjects has to take the Quiz before getting all the questions correct. Quiz errors 1 and Quiz errors 2 denotes the number of errors a subject makes when she takes the Quiz the first and second time respectively. Session denotes session fixed effects, which are included in all regressions.

Table S8: Determinants of subjects’ actions with SEs clustered at the session level

<table>
<thead>
<tr>
<th>Treatments</th>
<th>B</th>
<th>N</th>
<th>R</th>
<th>RN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Var.: Action</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>1.226 (2.504)</td>
<td>2.832 (1.614)</td>
<td>13.38*** (2.485)</td>
<td>36.80*** (8.774)</td>
</tr>
<tr>
<td>Clustering</td>
<td>-0.202 (0.747)</td>
<td>1.205* (0.514)</td>
<td>-2.080* (0.907)</td>
<td>-0.171 (1.478)</td>
</tr>
<tr>
<td>Betweenness</td>
<td>4.672 (2.605)</td>
<td>1.550 (1.531)</td>
<td>-10.85*** (3.144)</td>
<td>-19.61** (7.433)</td>
</tr>
<tr>
<td>Eigenvector</td>
<td>7.147 (4.451)</td>
<td>1.459 (1.787)</td>
<td>-3.636 (4.043)</td>
<td>-2.528 (11.48)</td>
</tr>
<tr>
<td>Community</td>
<td>0.550 (0.393)</td>
<td>0.464 (0.286)</td>
<td>0.658 (0.439)</td>
<td>2.018* (0.797)</td>
</tr>
<tr>
<td>Payoff</td>
<td>-0.234*** (0.0300)</td>
<td>-0.126*** (0.0177)</td>
<td>-0.303*** (0.0352)</td>
<td>-0.950*** (0.177)</td>
</tr>
<tr>
<td>L1.action</td>
<td>0.609 (0.495)</td>
<td>0.134 (0.345)</td>
<td>1.509** (0.575)</td>
<td>0.834 (0.945)</td>
</tr>
<tr>
<td>L2.action</td>
<td>0.922* (0.428)</td>
<td>0.778** (0.300)</td>
<td>0.371 (0.573)</td>
<td>2.327 (1.251)</td>
</tr>
<tr>
<td>L3.action</td>
<td>0.876* (0.413)</td>
<td>0.607* (0.299)</td>
<td>0.459 (0.505)</td>
<td>2.318* (1.090)</td>
</tr>
<tr>
<td>------------------</td>
<td>----------------</td>
<td>----------------</td>
<td>---------------</td>
<td>----------------</td>
</tr>
<tr>
<td>L4.action</td>
<td>1.357*** (0.387)</td>
<td>0.847** (0.299)</td>
<td>-0.263 (0.486)</td>
<td>-0.310 (0.767)</td>
</tr>
<tr>
<td>L5.action</td>
<td>0.642 (0.390)</td>
<td>0.324 (0.304)</td>
<td>-0.398 (0.513)</td>
<td>-1.726 (0.970)</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.169 (0.376)</td>
<td>0.0345 (0.288)</td>
<td>-0.0692 (0.445)</td>
<td>-0.713 (0.831)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0130 (0.0185)</td>
<td>0.00189 (0.0166)</td>
<td>-0.0305 (0.0220)</td>
<td>0.0211 (0.0426)</td>
</tr>
<tr>
<td>Trust</td>
<td>0.155 (0.365)</td>
<td>-0.0176 (0.298)</td>
<td>0.0216 (0.505)</td>
<td>-0.721 (0.795)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.0722 (0.142)</td>
<td>-0.0707 (0.106)</td>
<td>0.0559 (0.174)</td>
<td>-0.781* (0.320)</td>
</tr>
<tr>
<td>Risk</td>
<td>-0.0246 (0.464)</td>
<td>0.0957 (0.268)</td>
<td>0.134 (0.435)</td>
<td>0.690 (0.844)</td>
</tr>
<tr>
<td>Links added</td>
<td>-1.645*** (0.290)</td>
<td>-1.166*** (0.210)</td>
<td>-0.512 (0.317)</td>
<td>-0.843 (0.704)</td>
</tr>
<tr>
<td>Total links removed</td>
<td>0.768*** (0.222)</td>
<td>0.132 (0.158)</td>
<td>0.912** (0.333)</td>
<td>-0.242 (0.398)</td>
</tr>
<tr>
<td>Proposals received</td>
<td>1.416*** (0.241)</td>
<td>0.801*** (0.170)</td>
<td>0.909*** (0.225)</td>
<td>0.674 (0.636)</td>
</tr>
<tr>
<td>Removals received</td>
<td>-0.445 (0.287)</td>
<td>0.0348 (0.182)</td>
<td>-0.584 (0.354)</td>
<td>0.110 (0.426)</td>
</tr>
<tr>
<td>Proposals approved</td>
<td>1.264*** (0.348)</td>
<td>1.156*** (0.286)</td>
<td>0.138 (0.417)</td>
<td>-0.0206 (0.826)</td>
</tr>
<tr>
<td>Proposals rejected</td>
<td>0.000763 (0.103)</td>
<td>0.0207 (0.0755)</td>
<td>0.00624 (0.129)</td>
<td>-0.255 (0.242)</td>
</tr>
<tr>
<td>Time 1</td>
<td>-0.0389 (0.0240)</td>
<td>0.0135 (0.0167)</td>
<td>-0.0587 (0.0360)</td>
<td>-0.0705 (0.0789)</td>
</tr>
<tr>
<td>Time 2</td>
<td>-0.0305 (0.0283)</td>
<td>-0.00429 (0.0217)</td>
<td>-0.00961 (0.0455)</td>
<td>0.118 (0.101)</td>
</tr>
<tr>
<td>Time 3</td>
<td>-0.0600 (0.0377)</td>
<td>-0.0658* (0.0270)</td>
<td>-0.0750 (0.0577)</td>
<td>-0.255* (0.129)</td>
</tr>
<tr>
<td>Mouse hover 1</td>
<td>0.00990 (0.0221)</td>
<td>-</td>
<td>0.155 (0.244)</td>
<td></td>
</tr>
<tr>
<td>Mouse drag 1</td>
<td>0.191 (0.284)</td>
<td>-</td>
<td>0.809 (1.391)</td>
<td></td>
</tr>
<tr>
<td>Mouse hover 2</td>
<td>0.0808 (0.0727)</td>
<td>-</td>
<td>0.0233 (0.166)</td>
<td></td>
</tr>
<tr>
<td>Mouse drag 2</td>
<td>1.781 (1.661)</td>
<td>-</td>
<td>-0.995 (0.608)</td>
<td></td>
</tr>
</tbody>
</table>
Table S9 shows the results of a logistic regression to investigate how a subject’s decision to propose a link to another subject depend on the recipient’s network position and previous action. We run a logistic regression with session and round fixed effects and standard errors clustered at the session level. The dependent variable is a dummy, proposal$_{ij}$, indicating whether subject $i$ makes a proposal to another subject $j$ in round $t + 1$ ($1 = \text{proposal made}$). We only include $i$-$j$ pairs that are not linked at round $t$, which explains the different number of observations for each treatment.

We include three independent variables for all four treatments: $d_i$ is the number of neighbors of $i$ in round $t$; $d_j$ is the number of neighbors of $j$ in round $t$; $d_{ij}$ is the number of common neighbors between $i$ and $j$ in round $t$. Furthermore, we control for the action taken by $j$ in round $t$ for the $R$ and $RN$ treatments because in these treatments reputational knowledge is available about everyone in the network. In treatments $B$ and $N$, the information about $j$’s

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mouse hover 3</td>
<td>-</td>
<td>-0.0134 (0.0690)</td>
<td>-</td>
<td>-0.0272 (0.223)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mouse drag 3</td>
<td>-</td>
<td>0.149 (0.256)</td>
<td>-</td>
<td>-0.607 (1.121)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quiz tries</td>
<td>0.134 (0.672)</td>
<td>-0.548 (0.511)</td>
<td>0.763 (0.829)</td>
<td>-1.044 (1.521)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quiz errors 1</td>
<td>-0.0795 (0.446)</td>
<td>0.207 (0.340)</td>
<td>-0.113 (0.628)</td>
<td>1.443 (0.894)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quiz errors 2</td>
<td>-0.313 (0.580)</td>
<td>0.487 (0.617)</td>
<td>-2.256* (1.140)</td>
<td>-2.136 (2.152)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.788 (1.852)</td>
<td>-2.378* (1.068)</td>
<td>-3.381 (2.029)</td>
<td>8.992* (4.171)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>658</td>
<td>722</td>
<td>802</td>
<td>756</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>132.7</td>
<td>188.9</td>
<td>114.0</td>
<td>39.66</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
action at time \( t \) is not available to \( j \) so we do not include the control in the main regressions, but, as a robustness check, we also run the same regressions including the control and the results are unchanged.

The results in Table S9 below show that the variable \( d_{ij} \) is highly significant only in the \( N \) treatment, which shows that the probability that a subject proposes a link to another subject in the \( N \) treatment is increasing in the number of common neighbors.

Table S9: Determinants of subjects’ link proposals with SEs clustered at the session level

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>B</th>
<th>N</th>
<th>N</th>
<th>R</th>
<th>RN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Var.: proposal(_{ij})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( d_i )</td>
<td>-0.240(*)</td>
<td>-0.247(*)</td>
<td>-0.192(*)</td>
<td>-0.210(**)</td>
<td>-0.204(**)</td>
<td>-0.155(**)</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.105)</td>
<td>(0.090)</td>
<td>(0.081)</td>
<td>(0.079)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>( d_j )</td>
<td>0.094(*)</td>
<td>0.006</td>
<td>-0.007</td>
<td>-0.076</td>
<td>0.089(*)</td>
<td>0.182(***)</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.048)</td>
<td>(0.065)</td>
<td>(0.059)</td>
<td>(0.038)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>( d_{ij} )</td>
<td>0.049</td>
<td>0.081</td>
<td>0.178(***)</td>
<td>0.217(***)</td>
<td>0.092</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.052)</td>
<td>(0.047)</td>
<td>(0.063)</td>
<td>(0.059)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>action(_j)</td>
<td>1.269(***)</td>
<td>1.050(***)</td>
<td>2.001(***)</td>
<td>1.762(***)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.091)</td>
<td>(0.122)</td>
<td>(0.389)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>6102</td>
<td>6102</td>
<td>6040</td>
<td>6040</td>
<td>3986</td>
<td>4138</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. * \( P < 0.05 \), ** \( P < 0.01 \), *** \( P < 0.001 \).

5.4 Visual summary

Here we present snapshots of representative sessions to give a visual summary of our findings.
In the baseline $B$, the level of cooperation is low leading to sparse networks and no association between cooperation and position in the social structure. The addition of global social knowledge in $N$ leads to a positive association between clustering and cooperativeness, but it has no impact on the aggregate level of cooperation and the structure of the network. The introduction of global reputational knowledge in the $R$ treatment leads to a sharp increase in cooperation level, payoffs, the emergence of cooperative hubs, and a very dense and clustered network. The presence of both global reputation and global social knowledge in $RN$ has no impact on the aggregate level of cooperation compared to $R$, but it has a distributional effect: it
allows cooperators to fully exploit the ability to form and remove connections by creating a separate community which effectively excludes defectors. RN is the only treatment where there is a significant gap in outcomes depending on community membership: individuals in community C1 tend to be more cooperative than individuals in C2 so C1 achieves a significantly higher cooperation level than C2, and within-community interactions produce a larger payoff for the community members of C1 compared to C2.

6 Stability

In this section we motivate our choice to focus our main analysis to rounds 6 to 13 by showing that subjects’ play becomes more stable from round 6 onwards.

Given the ordered communities (by size) in each round, we compare membership of corresponding communities in consecutive rounds to see if the communities stabilize over time. We first define two stability metrics, and then use them to investigate when community membership becomes stable.

The first stability metric we define is C1 Stable: it captures the stability of the largest community (C1) in any given round by comparing the membership of C1 in round t to that of the C1 community in the t − 1 and t − 2 rounds respectively. If the C1 community in at least one round between t − 1 and t − 2 has at most two changes in membership compared to the C1 community at t, then we set the value of C1 Stable to 1 for round t, otherwise we set it to 0.

The second stability metric we define is Any Stable, which expands the definition of C1 Stable by extending the comparison to more communities. The Any Stable metric compares the membership of a given community (C1, C2, or C3) in round t to that of any other community in the t − 1 and t − 2 rounds. If the difference is less than 2 for any comparison, then we set the value of Any Stable to 1 for round t, otherwise we set it to 0. If any community in at least one round between t − 1 and t − 2 has at most two changes in membership compared to the given
community at \( t \), then we set the value of Any Stable to 1 for round \( t \), otherwise we set it to 0.

We compute the values of both metrics for every community in every round of the game, and aggregate it by computing the mean value over the \([13 - x, 13]\) range of rounds for each treatment. We select the largest integer \( x \) such that the means of both the \( C1 \) Stable and the Any Stable metrics are above 0.5 with the additional constraint that \( x < 9 \) so that the history of the previous 5 actions is already available to subjects. Moreover, we require that if the metrics are above 0.5 in the \([13 - x, 13]\) range of rounds, then they must be above 0.5 in the \([13 - y, 13]\) range, where \( y < x \). The largest \( x \) that satisfies these criteria is \( x = 7 \), and Table S10 shows the values of the \( C1 \) Stable and the Any Stable metrics for each community in all 4 treatments.

Table S10: Stability metrics for communities \( C1 \) and \( C2 \) in each treatment

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Community</th>
<th>Size</th>
<th>( C1 ) Stable</th>
<th>Any Stable</th>
</tr>
</thead>
<tbody>
<tr>
<td>( B )</td>
<td>1</td>
<td>6.6</td>
<td>0.55</td>
<td>0.73</td>
</tr>
<tr>
<td>( B )</td>
<td>2</td>
<td>5.0</td>
<td>0.79</td>
<td></td>
</tr>
<tr>
<td>( N )</td>
<td>1</td>
<td>6.8</td>
<td>0.59</td>
<td>0.71</td>
</tr>
<tr>
<td>( N )</td>
<td>2</td>
<td>4.7</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>( R )</td>
<td>1</td>
<td>8.1</td>
<td>0.52</td>
<td>0.63</td>
</tr>
<tr>
<td>( R )</td>
<td>2</td>
<td>4.9</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>( RN )</td>
<td>1</td>
<td>8.0</td>
<td>0.5</td>
<td>0.57</td>
</tr>
<tr>
<td>( RN )</td>
<td>2</td>
<td>4.9</td>
<td>0.57</td>
<td></td>
</tr>
</tbody>
</table>

Mean values of the \( C1 \) Stable and Any Stable metrics in rounds \([6, 13]\). Size is the mean size of the communities in each treatment. By definition the \( C1 \) Stable metric is only available for the \( C1 \) community.
7 Robustness Checks

In this section we check that our results are robust to the inclusion of the sessions with dropped out subjects.

There are a total of 2 sessions (out of 30) in which subject(s) drop out during the game. In treatment $R$, four subjects subsequently dropped out during the game in rounds 1, 2, 5 and 9. In treatment $RN$, one subject dropped out in round 3. UbiquityLab actively prevents drop-outs caused by temporary network problems, and any temporarily disrupted connection is automatically restored upon detection. However, we cannot circumvent issues such as the permanent loss of power or Internet connection, the crash of a subject’s browser or operating system, and voluntary termination. In the event of a drop-out, UbiquityLab automatically pauses the game at the end of the affected stage, notifies remaining subjects about the drop-out(s), and resumes the game after removing the subject who dropped out.

In this section, we re-run the analyses in the main text after including the data collected in these two sessions with drop-outs, and show that our results are robust to the inclusion of this additional incomplete data.

At the aggregate level, Figure S11 shows that the evolution of the cooperation level, average payoffs, density and clustering of the network in the different treatments is essentially unchanged compared to Figure 1 in the main text. As it is the case without the sessions with drop-outs, treatments $R$ and $RN$ with global reputational knowledge have a higher level of cooperation, payoff, density and clustering than treatments $B$ and $N$ with only local reputational knowledge. There is no significant difference for any of the metrics between $RN$ and $R$, and no significant difference for any of the metrics between $B$ and $N$. 
Figure S11: (a) Cooperation level, (b) average payoff, (c) density, and (d) clustering over 13 rounds of play for treatments B (yellow), N (red), R (green) and RN (blue) after including the “drop-out” sessions. Analyses are based on aggregated data at the session level after round 5. Here we only present the P-values for significant comparisons of the Kruskal-Wallis test and/or the Dunn’s test (with the Benjamini-Hochberg adjustment with a 5% false discovery rate): (a) Cooperation level: K-W: $P = 0.010$; Dunn’s: RN vs. B, $P = 0.021$; R vs. B, $P = 0.019$; R vs. N, $P = 0.021$. (b) Average payoff: K-W: $P = 0.017$; Dunn’s: RN vs. B, $P = 0.033$; RN vs. N, $P = 0.036$; R vs. B, $P = 0.038$; R vs. N, $P = 0.029$. (c) Density: K-W: $P = 0.003$; Dunn’s: RN vs. B, $P = 0.009$; RN vs. N, $P = 0.015$; R vs. B, $P = 0.008$; R vs. N, $P = 0.009$. (d) Global clustering: K-W: $P = 0.005$; Dunn’s: RN vs. B, $P = 0.013$; RN vs. N, $P = 0.016$; R vs. B, $P = 0.014$; R vs. N, $P = 0.025$.

At the community level, all the results in the main text are substantially unchanged. As in the main analysis, we use the Mann-Whitney test to compare the largest community $C_1$ and the second largest community $C_2$ within each treatment. $RN$ remains the only treatment in which $C_1$ is more cooperative than $C_2$ ($P = 0.009$). Moreover, $RN$ is the only treatment where a member of $C_1$ achieves a higher average payoff from an interaction with a neighbor within community $C_1$ than a member of $C_2$ achieves from an interaction with a neighbor in $C_2$ ($P = 0.009$). Moreover, only in the $RN$ treatment, members of $C_1$ remove significantly more links than those of $C_2$ ($P = 0.046$), members of $C_2$ receive significantly more removals than those of $C_1$ ($P = 0.001$), and members of $C_2$ receive significantly more proposal rejections than those of $C_1$ ($P = 0.006$). Additionally, members of $C_2$ receive significantly more proposal rejections than those of $C_1$ ($P = 0.046$) in the $R$ treatment once we include the problematic session with 4 dropped out subjects.
8 Experimental Instructions (for treatment $B$)$^1$

General rules$^2$  1/7

There are 3 parts to the Experiment:

- Instructions
- Experiment
- Final Questionnaire

You will earn $2$ for sure only if you complete the Experiment and the Final Questionnaire. In addition, you can earn Experimental Points (EP) that will be converted into real earning in dollars. We expect the average total earning to be within the $4 - 7$ range, but your actual earnings may vary considerably depending on your performance.

The expected duration of the Experiment is about 45 minutes, and you need to fully dedicate your time to this Experiment for the next 45 minutes. If you exit at any point before completion, you will not receive any earnings.

The aim of this Experiment is to study how individuals make decisions in certain contexts. You will make decisions that will affect the amount of points you earn and the amount of points other Turkers earn.

All your decisions will remain completely confidential. We will not disclose your Turker ID or any other information that may allow others to identify you. Each Turker will be assigned a one-letter ID that is kept the same throughout the Experiment. ID assignments are random and carry no meaning.

You will be asked to take a Quiz later to ensure that you understand the Instructions. If you cannot pass the Quiz within 3 tries, you will not be able to participate in the Experiment.

---

$^1$Instructions for the other three treatments are available upon request from the authors.

$^2$Each section heading corresponds to a web page of the Instructions.
The expected average time before you reach the Quiz is 15 minutes, and it is important that you read through the Instructions carefully. Note that each participant is shown exactly the same Instructions.

Please click the ‘Next’ link below to continue.

**The game 2/7**

You and 12 other Turkers will play several rounds of a “game”. Each round is the same and consists of 3 stages.

In Stages 1 and 2, you can form and cut links with any of the other Turkers, which we will explain shortly. If you are linked with another Turker then that Turker is a “neighbor”.

In Stage 3, you choose either action A or action B, and the choice of action A or B applies to all your neighbors. Action A is color-coded in green and action B is color-coded in blue. The colors are only a visual aid to distinguish the actions and have no meaning. You get points for the action you choose and the action each of the other Turkers chooses, in the following way:

You get 0 points if you are not linked with another Turker regardless of your choice of action.

The number of points you get depends on the actions you and your neighbor choose, according to the table below:

<table>
<thead>
<tr>
<th></th>
<th>You</th>
<th>Neighbor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>A</td>
<td>3</td>
<td>-5</td>
</tr>
<tr>
<td>B</td>
<td>5</td>
<td>-3</td>
</tr>
</tbody>
</table>

This is what the table says:

- If you choose A and the neighbor chooses A, you get 3 points

- If you choose A and the neighbor chooses B, you get −5 points
• If you choose B and the neighbor chooses A, you get 5 points

• If you choose B and the neighbor chooses B, you get −3 points

At the end of each round you will see a summary of the number of points you get with each of the other Turkers.

You will play 13 rounds of this game for sure. After round 13, there is a 50% chance that the game will terminate in the following round. In other words, in every round after round 13 the computer will “flip a coin” and if the outcome is “Heads” then the game will terminate.

Please click the ‘Next’ link below to continue to a detailed description of Stage 1.

Stage 1 - Link decisions 3/7

In Stage 1, you decide which Turkers you want to link with.

We will explain each part of the interface separately and you will see the whole interface in the Tour later.

Top-right of the screen The first row shows the current stage and the current round you are in. You also see a countdown timer that indicates the time you have left to make your decisions. In every round, you have 70 seconds to complete Stage 1.

The second row reminds you of the actions you have chosen in last 5 rounds. For example, the sequence below means that you chose action A in last round (the rightmost green square), action B two rounds ago (blue square in the 2nd slot counting from the right), action B three rounds ago (blue square in the 3rd slot counting from the right), etc.
Note that if you do not have any neighbor in a round, then you cannot choose an action in that round, and your round action is denoted by a gray box.

There is also a “Table of Points” link: you can move your mouse pointer over it to show the table of points you saw previously. Try it now!

**Top-left of the screen**  This figure visualizes your current neighbors.

![Neighborhood Diagram]

The neighbors you have at the start of each round are the same as the neighbors you had at the end of the previous round. The links are reciprocal so if you are linked to Turker G then Turker G is linked to you.

Each circle denotes a Turker with an ID. The “You” circle is always positioned at the center. For example, above you are linked with H, P, and G.

The colors of the circles denote the action chosen by each Turker in the previous round. For example, in the above figure Turker P chose action A and Turker H chose action B in the previous round.

Note that no links exist between Turkers in Stage 1 of Round 1, so only the “You” circle will be displayed.

**Middle-left of the screen**  This table allows you to make your decisions in Stage 1.
You can cut a link to any neighbor by ticking the corresponding box under the “Unlink” column.

You can also propose a link to any other Turker by ticking the corresponding box under the “Link” column. There is no limit to how many boxes you can tick, and you can also choose not to cut or propose any link by leaving all the boxes unticked.

The table has 5 columns, from left to right:

Neighbor: lists the IDs of Turkers who are currently linked with you.

History: lists last 5 actions chosen by each of your neighbors.

Unlink: allows you to cut your link to any of your neighbors. For example, ticking the box in the first row will cut your link to Turker H.

Others: lists the IDs of Turkers who are not currently linked with you.

Link: allows you to propose a link to any of the Turkers you are not linked with. For example, ticking the box in the first row will propose a link to Turker E.

The color-codings of the other Turkers’ actions are the same as before. The green box A denotes the choice of action A. The blue box B denotes the choice of action B. The gray box □ denotes
that the Turker did not have any neighbor in that round, and therefore the Turker did not choose an action. For example, no action was chosen by Turker P five rounds ago.

Note that in Round 1 all the Turkers will be listed under "Others" because no links exist between Turkers.

**Bottom-left of the screen**  This figure shows you the Turkers you are not currently linked with. Each circle denotes a Turker with an ID.

**Bottom-right of the screen**  The text reminds you about the decisions you need to make in Stage 1. You can propose new links and cut existing links, or you can choose not to propose or cut any links. In either case, you need to click the "Submit" button to confirm your decisions.
Please click the ‘Next’ link below to continue to a detailed description of Stage 2.

**Stage 2 - Yes/No responses 4/7**

In Stage 2, you decide whether to accept or reject link proposals from other Turkers.

**Top-right of the screen**  In every round, you have 45 seconds to complete Stage 2.

The second row is the same as in Stage 1: your actions in last 5 rounds and the “Table of Points” link.

**Top-left of the screen**  This is the same as in Stage 1: a figure that shows your current neighbors. Note that the figure is not updated yet with yours and others’ link decisions in Stage 1. The colors of the circles denote the action chosen by each Turker in the previous round.
Middle-left of the screen  This table allows you to make your decisions in Stage 2.

<table>
<thead>
<tr>
<th>Neighbor</th>
<th>History</th>
<th>Unlink</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>P</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>G</td>
<td>A</td>
<td>B</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Others</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td></td>
</tr>
<tr>
<td>R</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td></td>
</tr>
<tr>
<td>S</td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>Y</td>
</tr>
<tr>
<td>V</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td></td>
</tr>
<tr>
<td>W</td>
<td></td>
</tr>
<tr>
<td>Z</td>
<td>Y</td>
</tr>
<tr>
<td>T</td>
<td></td>
</tr>
</tbody>
</table>

The first three columns from the left ("Neighbor", "History", "Unlink") are the same as in Stage 1.

The “Others” column lists the Turkers you are not linked with.

Now look at Turkers R, K and Z: under the "Link" column a ”Y/N” ("Y" for Yes, ”N” for No) button appears. This means that R, K and Z have sent you a link proposal. For each proposal, you need to click on ”Y” to accept it or ”N” to reject it. In the example above, you have chosen to accept the proposal from R and reject the proposal from K, but you have not responded yet to the proposal from Z.

Note that your choice to accept or reject a proposal is highlighted in black.

Bottom-left of the screen  This is the same as in Stage 1: a figure that shows the Turkers you are not linked with. Note that the figure is not updated yet with yours and others’ link decisions in Stage 1.
**Bottom-right of the screen**  The first 3 rows remind you of your responses.

Before you press "Submit", you can change your responses and the text in the second and third rows will be updated accordingly.

You should click the "Submit" button after you have responded to all the proposals. If you do not respond to every proposal by the end of the stage, the computer will automatically reject any proposal that you have not responded to.

Note that it is also possible that no Turker proposes to link with you in Stage 1. In such case you will see the message below and you will need to wait for the other Turkers to complete Stage 2.
Please click the ‘Next’ link below to continue to a detailed description of Stage 3.

**Stage 3 - Action choice 5/7**

In Stage 3, you choose either action A or action B.

**Top-right of the screen**  In every round, you have 25 seconds to complete Stage 3.

The second row shows your actions in the last 5 rounds. Please move your mouse pointer over the "Table of Points" link to remind yourself about how you get points.

**Top-left of the screen**  This figure shows your current neighbors after Stage 1 and 2. Note that the figure is now updated with yours and the others’ decisions in the previous stages. The colors of the circles denote the action chosen by each Turker in the previous round.
Middle-right of the screen  This table shows your neighbors, the Turkers you are not linked with, and your neighbors’ actions in last 5 rounds. Note that the table is updated with yours and the others’ decisions in the previous stages.

<table>
<thead>
<tr>
<th>Neighbor</th>
<th>History</th>
<th>Unlink</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>A</td>
<td>B A B B</td>
</tr>
<tr>
<td>P</td>
<td>A A A B</td>
<td>A B A</td>
</tr>
<tr>
<td>G</td>
<td>A A A B</td>
<td>A B A</td>
</tr>
<tr>
<td>R</td>
<td>A A B A</td>
<td>A B A</td>
</tr>
<tr>
<td>Z</td>
<td>A A B B</td>
<td>A B A</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Others</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td></td>
</tr>
<tr>
<td>S</td>
<td></td>
</tr>
<tr>
<td>K</td>
<td></td>
</tr>
<tr>
<td>V</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td></td>
</tr>
<tr>
<td>W</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td></td>
</tr>
</tbody>
</table>

Bottom-left of the screen  This figure shows the Turkers you are not linked with. Note that the figure is now updated with yours and others’ decisions in the previous stages.
**Bottom-right of the screen**  This is where you choose your action in Stage 3 by clicking either the A or B button.

Once an action is chosen, the "Invalid" text will change to indicate your choice. Note that if you do not click any button then the computer will choose action B by default. You click the "Submit" button to confirm your choice.

Please choose an action towards all your neighbors:

A  B

Press 'Submit' to confirm that your action is: invalid

Submit

Note that it is possible that you are not linked with any Turker (i.e. you have no neighbor) as the result of everyone’s earlier decisions. In such case, you will instead see the message below, and you should click the 'Submit' button to continue.

You are not linked with any Turker in this round
Please press 'Submit' to continue

Submit

Please click the ‘Next’ link below to continue.

**Round results**  6/7

After Stage 3, you will see a summary of the points you got with each of the other Turkers in the round.
Top-right of the screen  In every round, you have 15 seconds to see the results.

The second row reminds you of the action you have just chosen.

Middle-right of the screen  This table summarizes the results of the current round.

There are 5 columns, from left to right:

Neighbor:  lists the IDs of Turkers who are linked with you.

Action:  lists the actions chosen by your neighbors.

Points:  lists the points you got with each of your neighbors.

Others:  lists the IDs of Turkers who are not linked with you.

Points:  lists the points you got with each of the Turkers who are not linked with you, which are always 0.
Please click the ‘Next’ link below to continue.

**Your bonus 7/7**

At the end of the Experiment, we will randomly select 6 rounds for payment. In each of these 6 rounds, we will randomly pick 2 other Turkers. Note that a Turker who was not linked with you can be picked, and in that case you will get 0 points for the game with that Turker.

To determine your bonus, we sum the number of points you got with each of the picked Turkers in each of the 6 rounds. The exchange rate from Experimental Points (EP) to US dollars is:

\[ 5 \text{ EP} = 1 \text{ dollar} \]

For example, the table below shows the payment details of an imaginary Turker.

<table>
<thead>
<tr>
<th>Selected round</th>
<th>Selected turker</th>
<th>Your action</th>
<th>Turker’s action</th>
<th>Your points</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>S</td>
<td>B</td>
<td>A</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>H</td>
<td>B</td>
<td>A</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>W</td>
<td>A</td>
<td>B</td>
<td>-5</td>
</tr>
<tr>
<td>5</td>
<td>P</td>
<td>unlinked</td>
<td>unlinked</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>W</td>
<td>A</td>
<td>A</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>R</td>
<td>A</td>
<td>B</td>
<td>-5</td>
</tr>
<tr>
<td>9</td>
<td>N</td>
<td>B</td>
<td>B</td>
<td>-3</td>
</tr>
<tr>
<td>11</td>
<td>E</td>
<td>B</td>
<td>A</td>
<td>5</td>
</tr>
<tr>
<td>11</td>
<td>Z</td>
<td>A</td>
<td>A</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>K</td>
<td>A</td>
<td>A</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>P</td>
<td>unlinked</td>
<td>unlinked</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>16</td>
</tr>
</tbody>
</table>

This imaginary Turker’s total earnings are:

\[
\text{Total earnings} = 200 + 1 \times \frac{16}{0.05} = 200 + 320 = 520 \text{ cents}
\]

Note that the total earnings include the $2 fixed fee and a $3.20 performance bonus.

In the unlikely event that we lose the connection to a Turker during the Experiment, the one-letter ID of that Turker will be removed in all subsequent rounds of the game and you will be
notified in the round when this happens. In the process of determining your bonus, we will not select any disconnected Turkers after the round in which we lose the connection to that Turker. It is possible to win an additional Bonus payment in the Final Questionnaire. We will explain this during the Final Questionnaire.

Please click the ‘Next’ link below to continue to the Tour.

**Supporting Information References**


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