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Inequality and Visibility of Wealth in Experimental Social Networks

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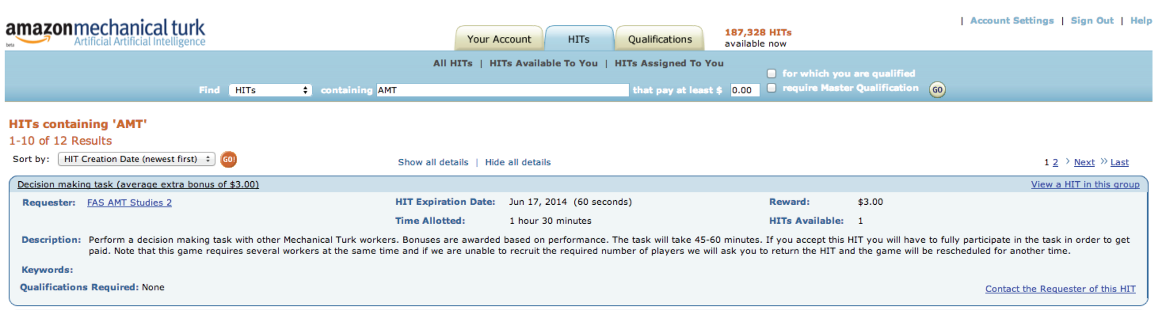
Methods

1. Experiment setting

There is a large design space for social experiments, including with respect to inequality, and, by necessity, we explore only a part of this space. We chose to focus on wealth visibility and initial wealth inequality and their impact on diverse social welfare outcomes in a public goods game setting, as the public goods game has become a standard paradigm for social interaction across fields. We also chose to explore wealth visibility in a setting of dynamic social network interactions wherein individuals could re-wire their connections. We implemented this feature primarily because, in our view, social capital (as captured by the density of social connections) is a key social welfare outcome of interest here, one that can co-evolve with cooperation and wealth inequality, as we show.

1.1. Participants recruitment

Subjects were recruited using Amazon Mechanical Turk (AMT) (shown below)[1,2]. They interacted anonymously in a virtual laboratory setting we created using bespoke software (a beta version of which, called "Breadboard," will soon be made publicly available)[3,4]. Subjects were not allowed to participate in more than one session of our experiments (the participants who participated in any parts of our experiments previously were temporarily "blacklisted" and no longer permitted to participate in future sessions of the same experiment). These online experiments were approved by the Yale University Human Subjects Committee.



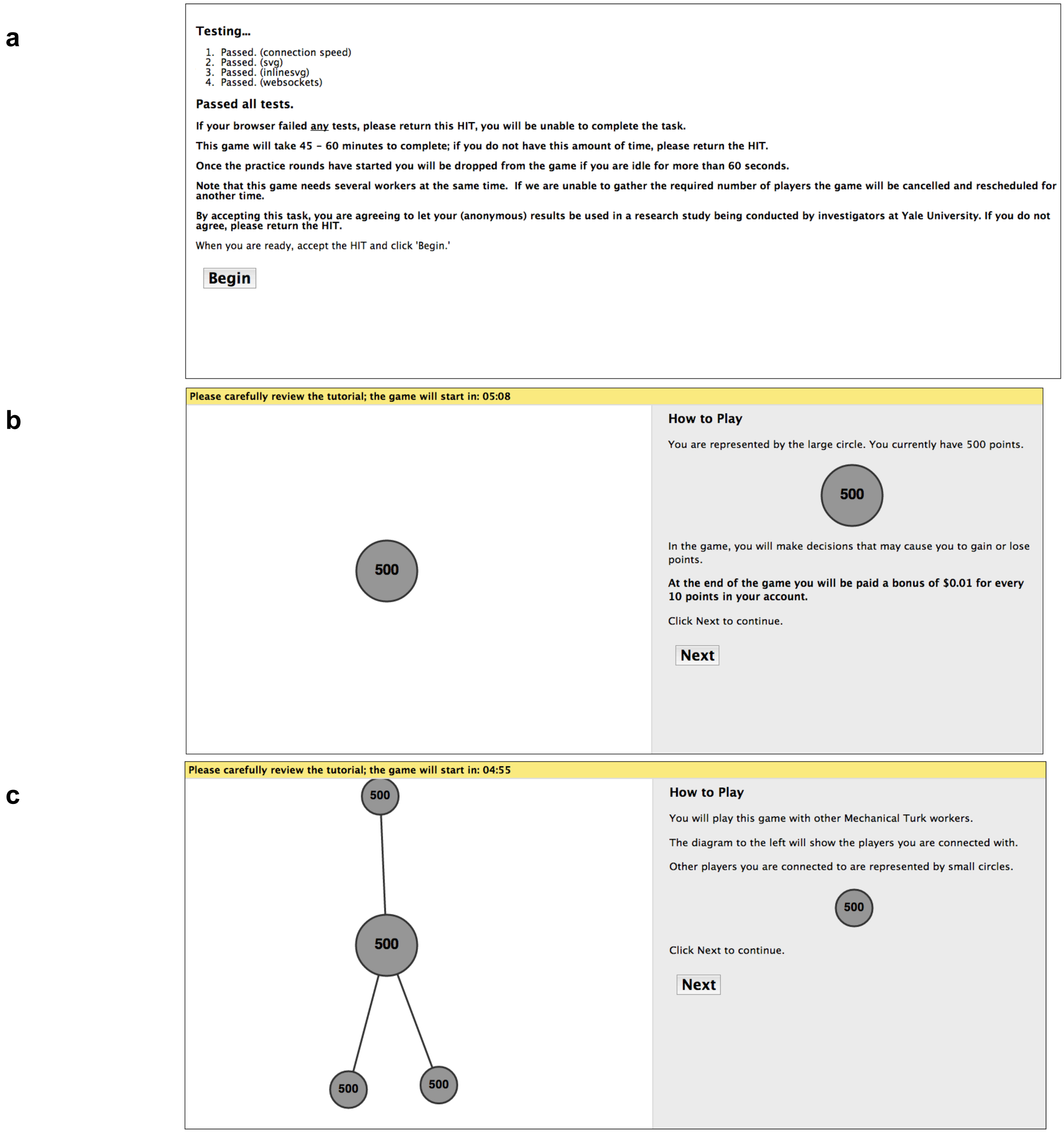
Screenshot for participant recruitment. We used Amazon Mechanical Turk (AMT) to recruit subjects from internet users from all over the world.

All 80 sessions were carried out between October and December 2013. The typical number of sessions that we implemented per day was 2 to 4. Each session lasted for a total of approximately 60 minutes (of which 30 minutes (SD = 7.13) was taken up in actual game play). At the end of each session, the subjects were paid a $3 show-up fee; each subject's final units, summed over all rounds, were converted into dollars at the exchange rate of 1 USD ($1) = 1,000 units. Overall, subjects typically earned approximately $6 (interquartile range [IQR]: $4.95 to $12.05) for their one-hour participation.

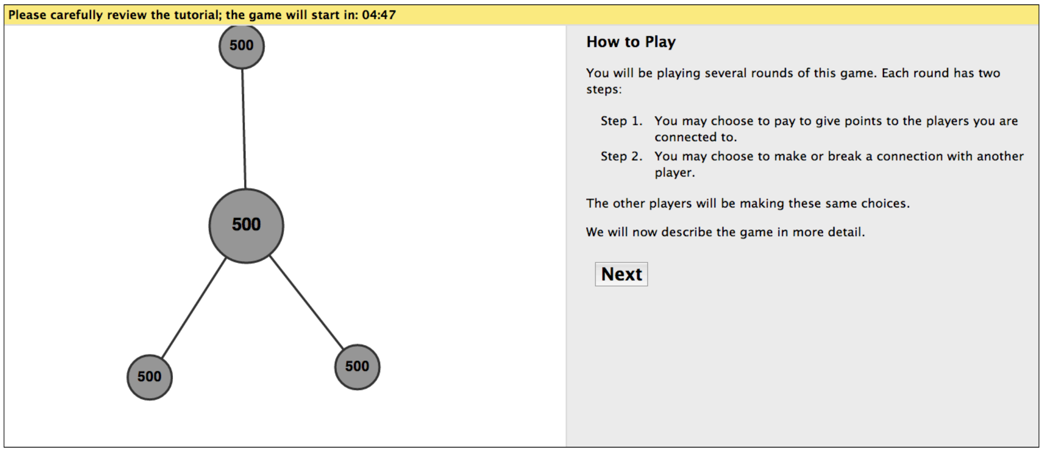
In each session, we aimed to recruit 13 – 25 subjects who could participate in the entire session, which included two training rounds and then ten actual rounds. Since we anticipated that some subjects might drop out during the training, we recruited 16 – 28 subjects (three more than the target range) at the beginning of each session and implemented the session regardless of the total number of the subjects participating if it was 16 or more. When the number of subjects who showed up reached 23 or the recruiting time period (up to 15 minutes) expired, we moved to the next steps: the explanation of the rules of the experiment (cooperation or defection, making a new connection or not, breaking an existing connection or not, etc.), and then the two training rounds. When the number of the subjects who showed up did not reach 16, the attempted session (practice rounds and actual rounds) was canceled, but the show-up fee was paid to the subjects.

1.2. Instruction (tutorial)

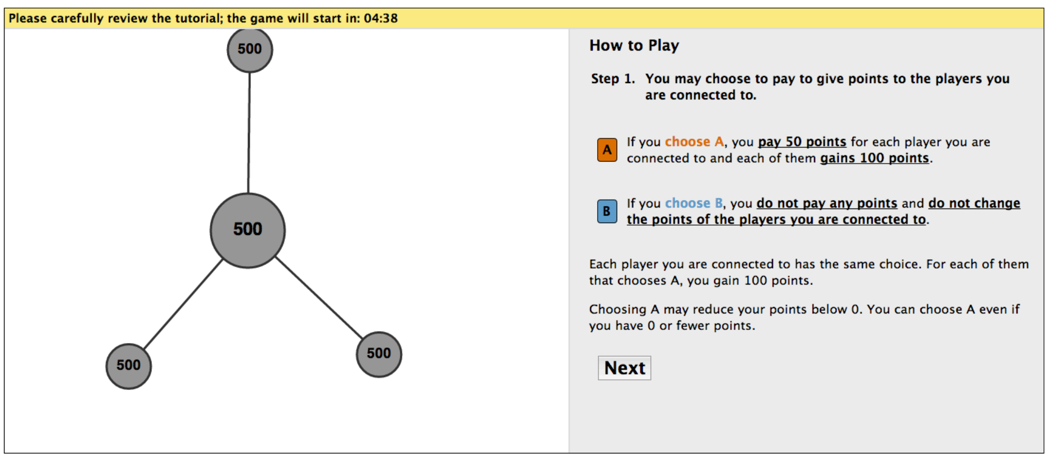
Before the practice rounds, we explained the experiments to the subjects. The exact sentences are shown below. Instructions in the practice rounds and in the actual rounds are shown in the screenshots (shown below).


a
Testing...
1. Passed. (connection speed)
2. Passed. (svg)
3. Passed. (inlinesvg)
4. Passed. (websockets)
Passed all tests.
If your browser failed any tests, please return this HIT, you will be unable to complete the task.
This game will take 45 - 60 minutes to complete; if you do not have this amount of time, please return the HIT.
Once the practice rounds have started you will be dropped from the game if you are idle for more than 60 seconds.
Note that this game needs several workers at the same time. If we are unable to gather the required number of players the game will be cancelled and rescheduled for another time.
By accepting this task, you are agreeing to let your (anonymous) results be used in a research study being conducted by investigators at Yale University. If you do not agree, please return the HIT.
When you are ready, accept the HIT and click 'Begin.'
Begin
b
Please carefully review the tutorial; the game will start in: 05:08
500
How to Play
You are represented by the large circle. You currently have 500 points.
500
In the game, you will make decisions that may cause you to gain or lose points.
At the end of the game you will be paid a bonus of $0.01 for every 10 points in your account.
Click Next to continue.
Next
c
Please carefully review the tutorial; the game will start in: 04:55
500
500
500
500
How to Play
You will play this game with other Mechanical Turk workers.
The diagram to the left will show the players you are connected with.
Other players you are connected to are represented by small circles.
500
Click Next to continue.
Next

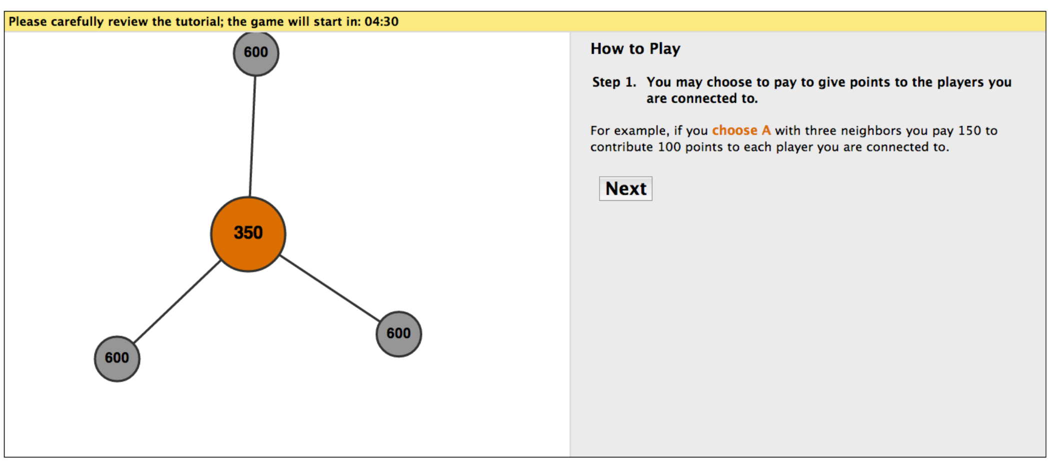
d


Please carefully review the tutorial; the game will start in: 04:47
500
500
500
500
How to Play
You will be playing several rounds of this game. Each round has two steps:
Step 1. You may choose to pay to give points to the players you are connected to.
Step 2. You may choose to make or break a connection with another player.
The other players will be making these same choices.
We will now describe the game in more detail.
Next

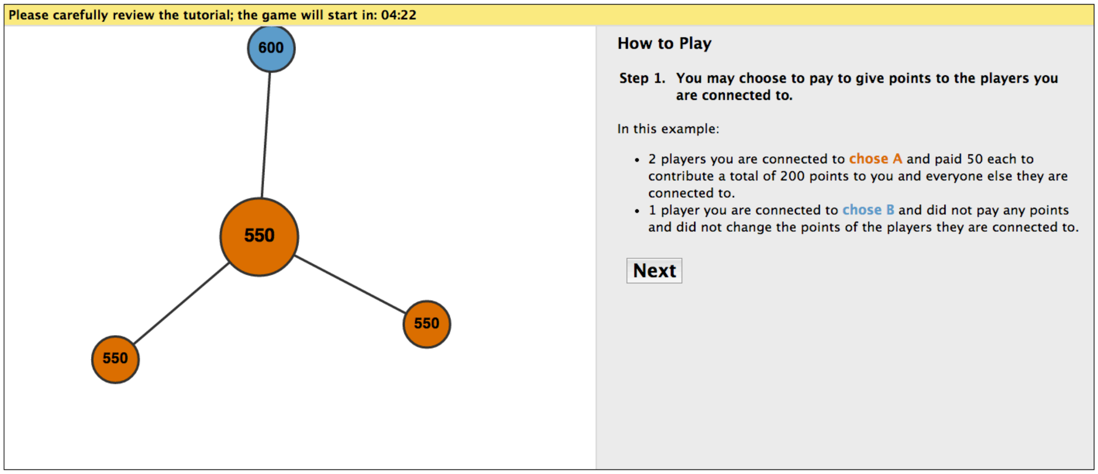
e


Please carefully review the tutorial; the game will start in: 04:38
500
500
500
500
How to Play
Step 1. You may choose to pay to give points to the players you are connected to.
A If you choose A, you pay 50 points for each player you are connected to and each of them gains 100 points.
B If you choose B, you do not pay any points and do not change the points of the players you are connected to.
Each player you are connected to has the same choice. For each of them that chooses A, you gain 100 points.
Choosing A may reduce your points below 0. You can choose A even if you have 0 or fewer points.
Next

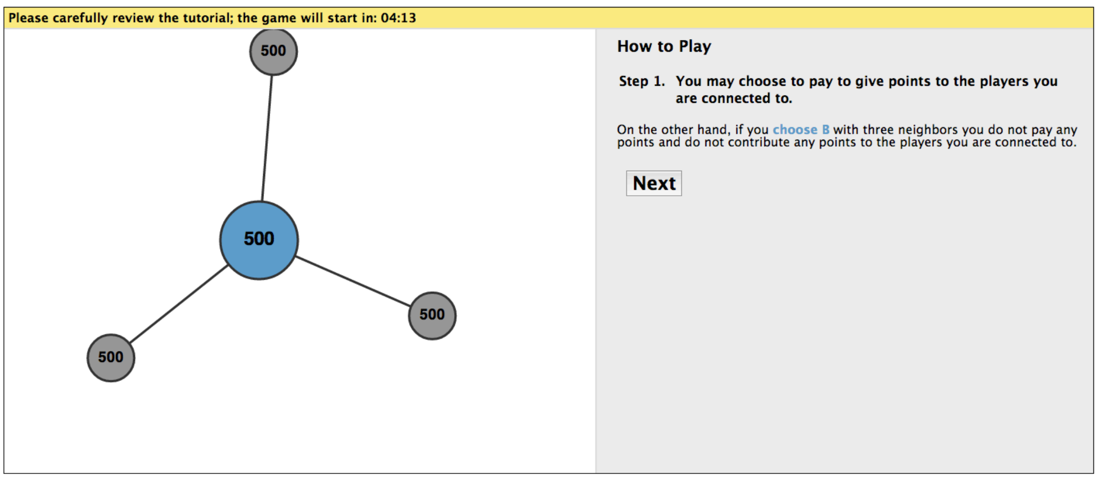
f


Please carefully review the tutorial; the game will start in: 04:30
600
350
600
600
How to Play
Step 1. You may choose to pay to give points to the players you are connected to.
For example, if you choose A with three neighbors you pay 150 to contribute 100 points to each player you are connected to.
Next

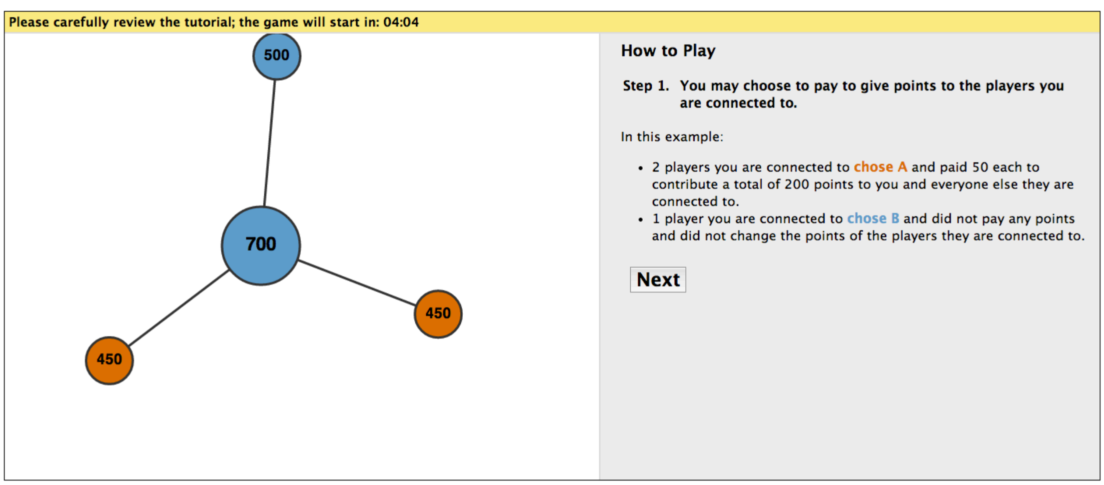
g


Please carefully review the tutorial; the game will start in: 04:22
600
550
550
550
How to Play
Step 1. You may choose to pay to give points to the players you are connected to.
In this example:
• 2 players you are connected to chose A and paid 50 each to contribute a total of 200 points to you and everyone else they are connected to.
• 1 player you are connected to chose B and did not pay any points and did not change the points of the players they are connected to.
Next

h


Please carefully review the tutorial; the game will start in: 04:13
500
500
500
500
How to Play
Step 1. You may choose to pay to give points to the players you are connected to.
On the other hand, if you choose B with three neighbors you do not pay any points and do not contribute any points to the players you are connected to.
Next

i


Please carefully review the tutorial; the game will start in: 04:04
500
700
450
450
How to Play
Step 1. You may choose to pay to give points to the players you are connected to.
In this example:
• 2 players you are connected to chose A and paid 50 each to contribute a total of 200 points to you and everyone else they are connected to.
• 1 player you are connected to chose B and did not pay any points and did not change the points of the players they are connected to.
Next

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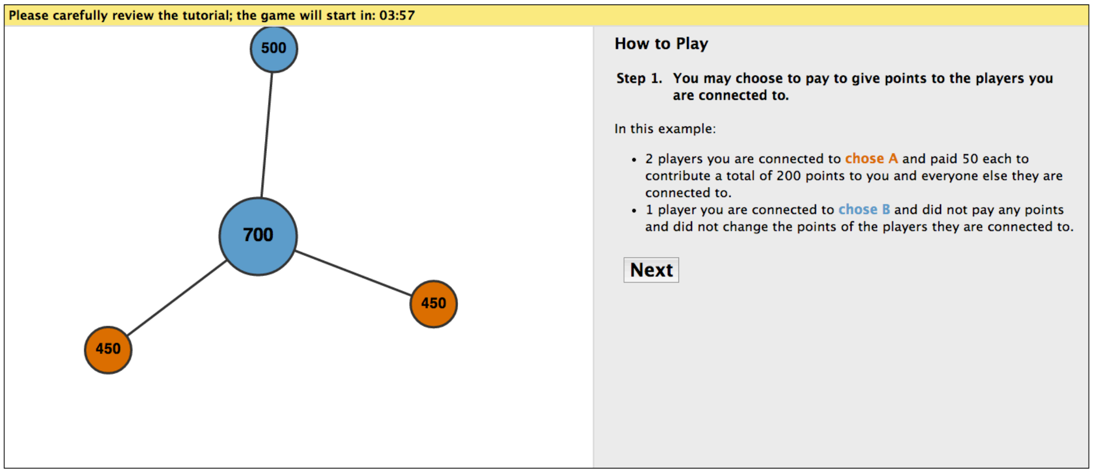
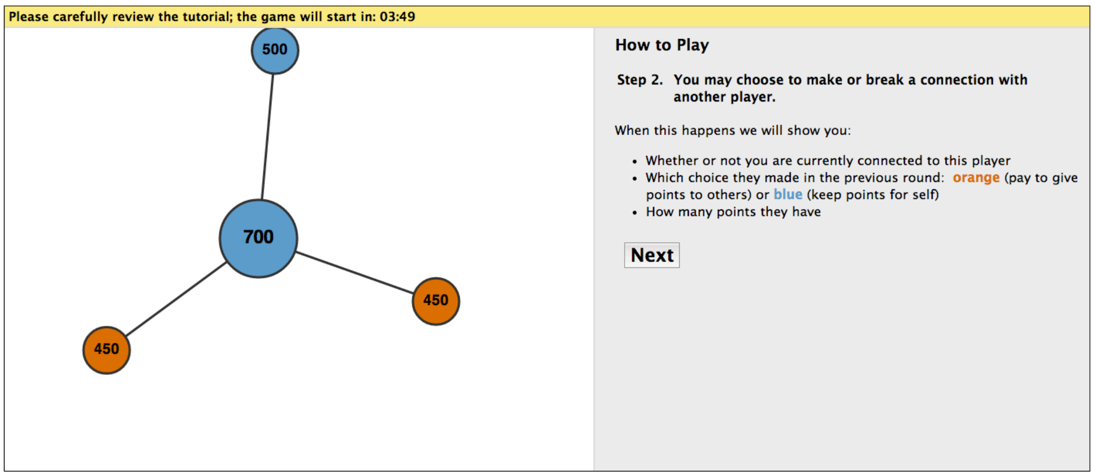
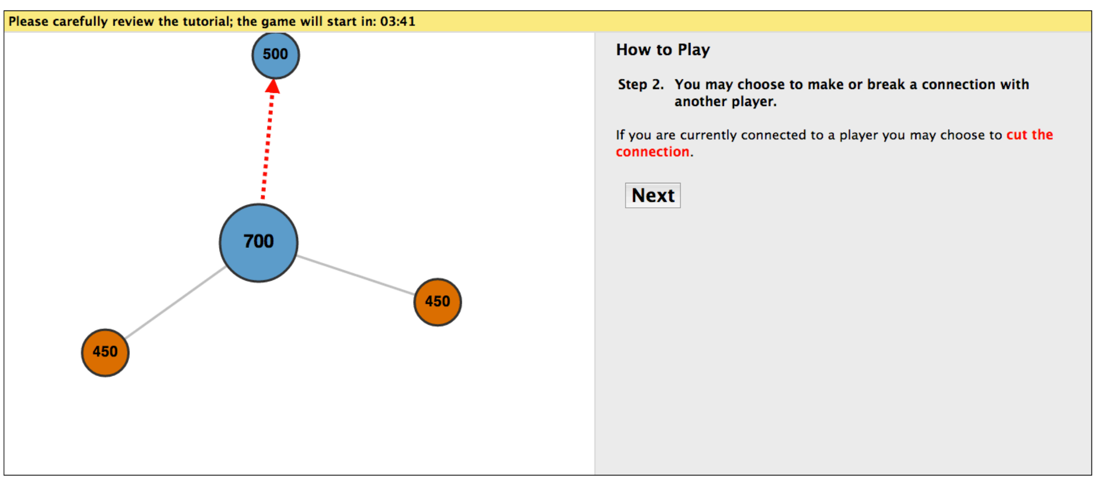
j



k



l



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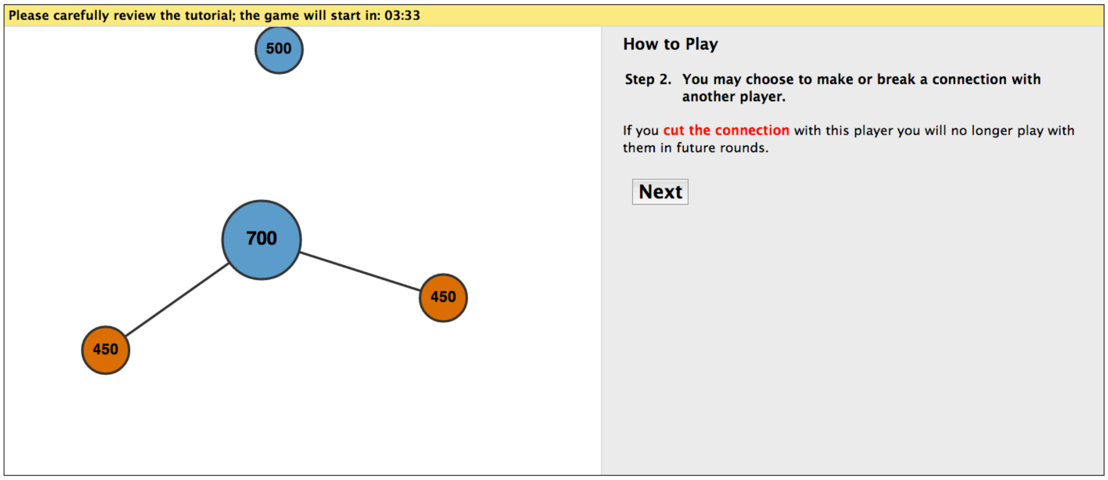
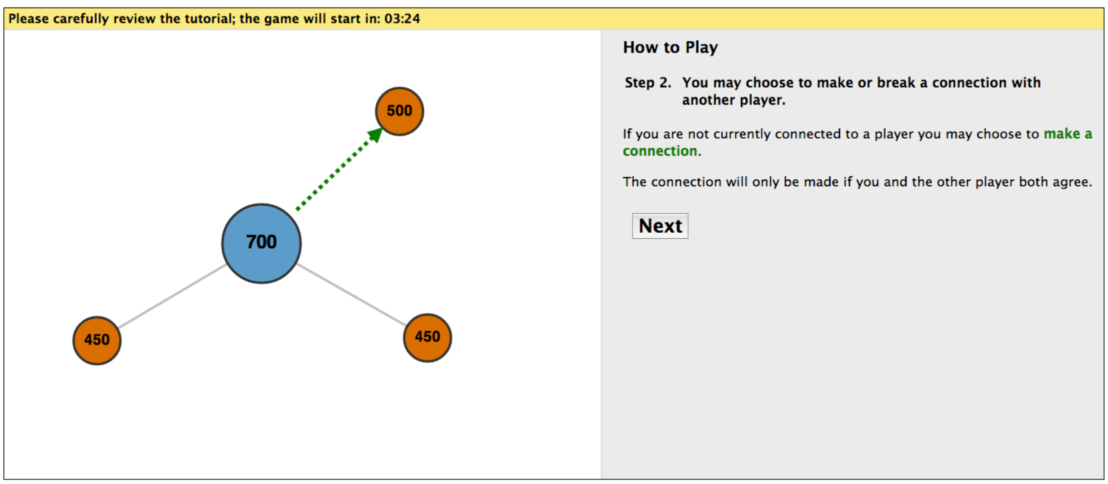
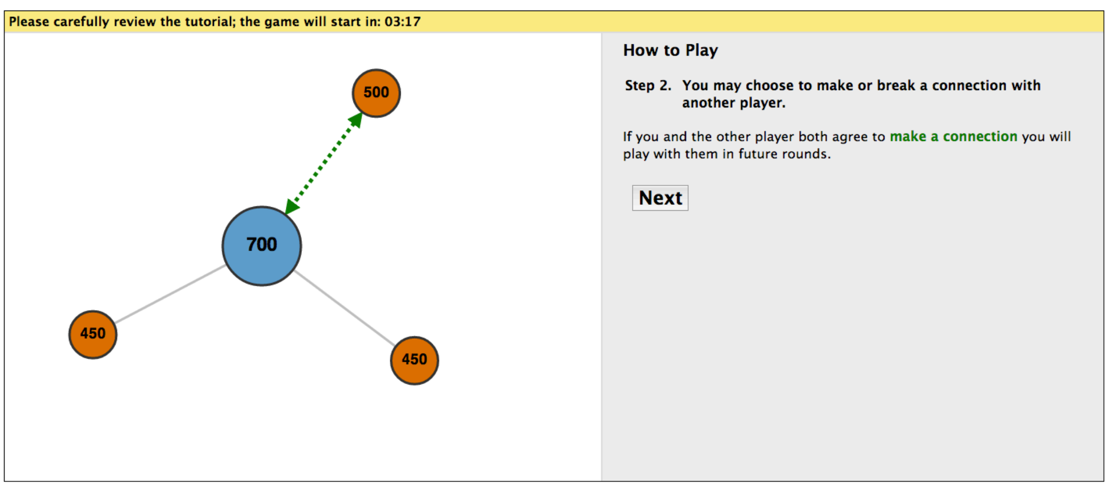
m



n



o



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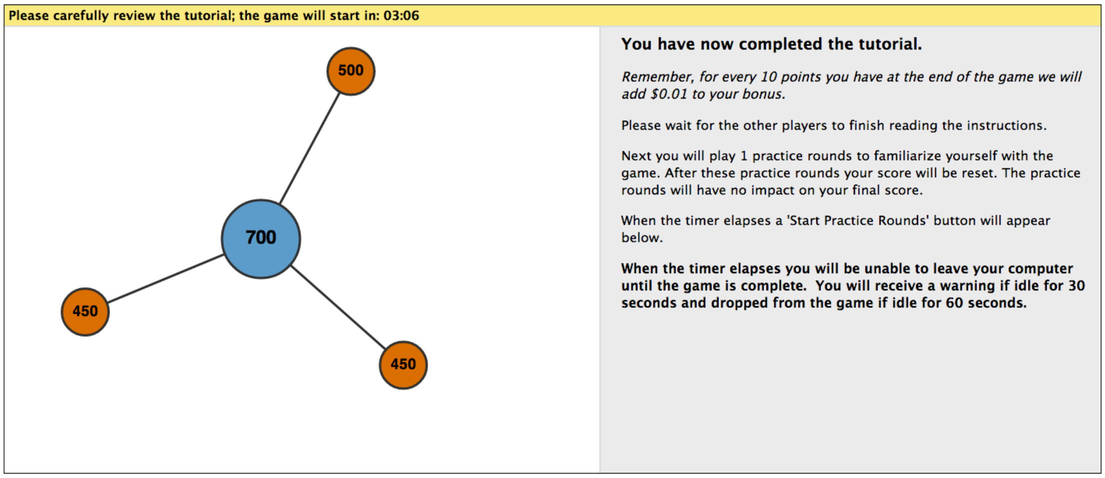
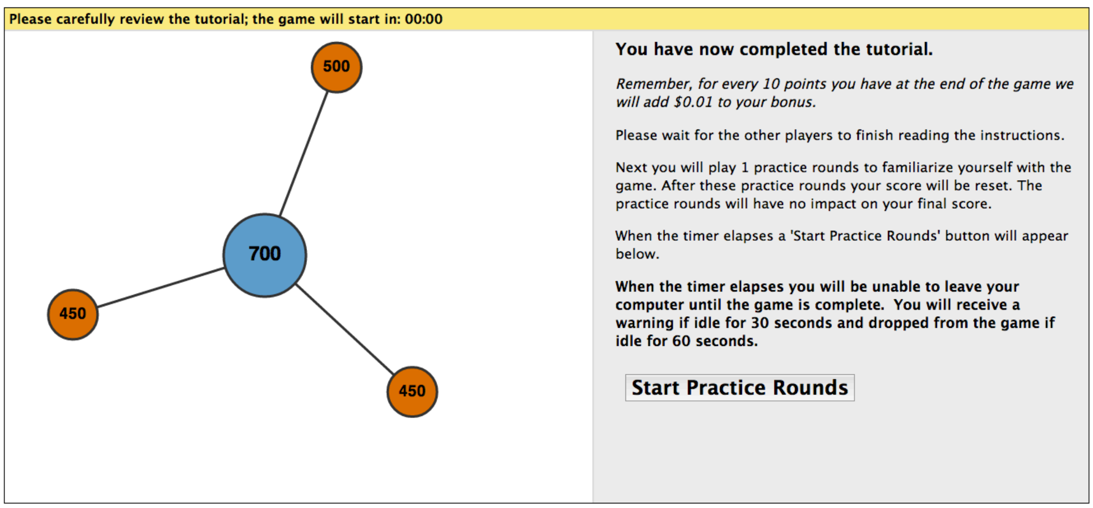
p



q



Screenshots of the tutorial (a – q). We show the screenshots of the visible condition. In the case of the invisible condition, the score (wealth) of the connecting neighbors is not shown in the tutorial (or later).

1.3. Practice rounds

The two training rounds were performed with the same conditions as the experiment (shown below). The interactions were repeated for two rounds. The setting for the training rounds was the same for all the sessions: (r, p, f, v) = (500, 500, 0.5, 0 or 1) (where r represents the amount of initial wealth among subjects in the "rich" group, p represents the amount of initial wealth among subjects in the "poor" group, f represents the fraction of the subjects in the rich group out of the entire subject sample, and v represents the condition of visibility of connected neighbors' wealth information where 1 is "visible" and 0 is "invisible"). We used the same visibility condition as the actual experiment the subject would experience, and subjects interacted with pre-programmed artificial intelligence players. The amount of wealth accumulated by the subjects at the end of the training rounds was not taken over into the actual rounds; wealth was re-set, according to the experimental design, at the start of the actual experiment. When the number of subjects finishing the training rounds did not reach at least 13, the attempted session was canceled.

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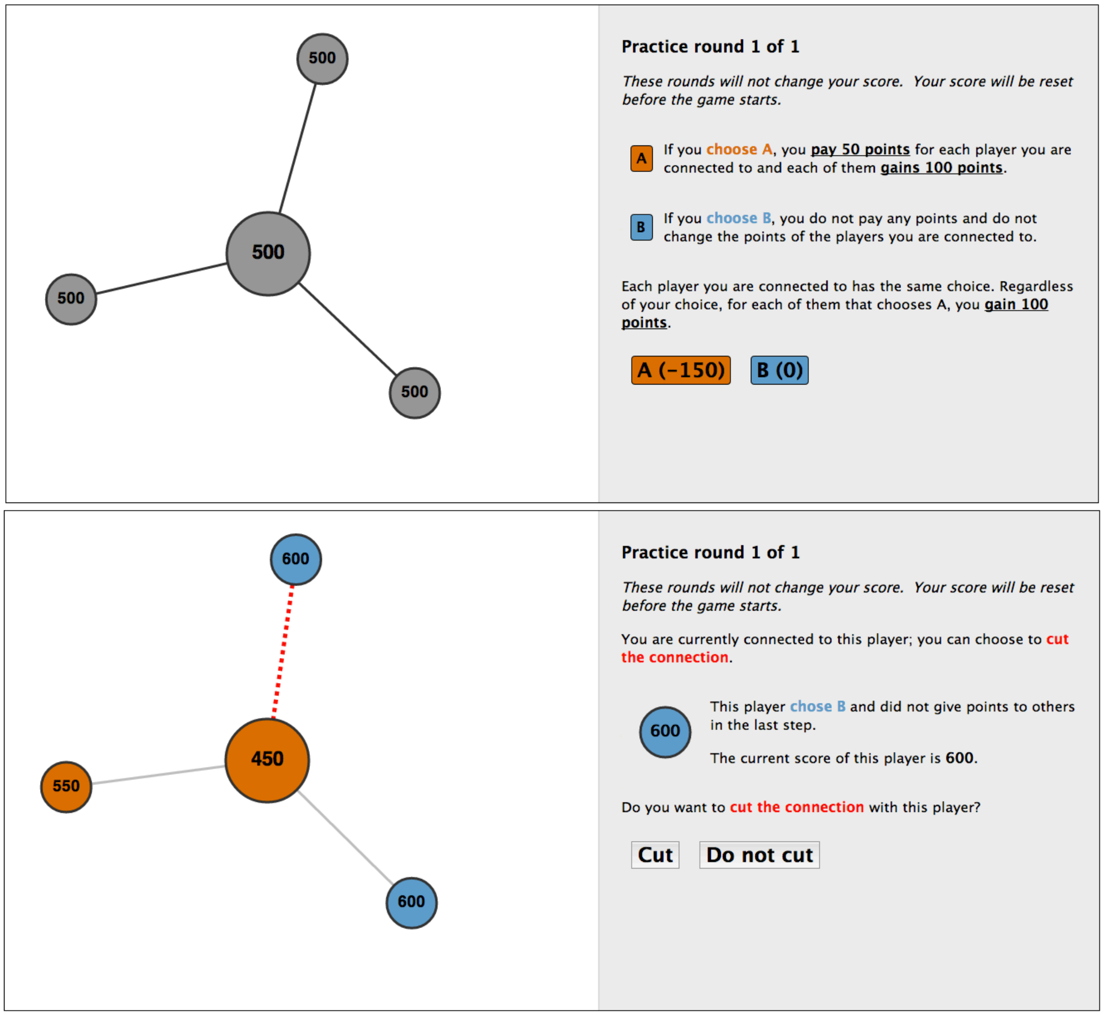
a
b



Screenshots of practice rounds. a, A focal subject (the larger circle in the center) is asked to choose to cooperate ("A [-150]") or to defect ("B [0]"). Since the focal subject is connected with three neighbors (the three smaller circles at the periphery), the focal subject needs to pay 50 × 3 = 150 units when the focal subject chooses "A" (to cooperate with connecting neighbors). All the circles are colored grey here because they have no record regarding their behavior in the prior move (this example is the first round). **b,** A focal subject and one of the connecting neighbors choose to cooperate, which results in –50 units for the focal subject. The change in the present units of the focal subject and the connecting neighbors are immediately reflected and shown in the screen (the neighbor's wealth is only shown in the visible condition). Then, in this example, a focal subject is asked whether to cut a randomly chosen tie ("Cut") or stay connected ("Do not cut") with one of the connecting neighbors (linked with the red dotted line). If the focal subject chooses to cut the tie, the tie dissolves without the approval of the connecting neighbor (there is unilateral decision-making for *breaking* a tie, but bilateral decision-making for *forming* a tie). Orange represents cooperation at the last round, and cyan represents defection at the last round.

1.4. Parameters in the actual rounds

We aimed to examine the effect of the visibility of connecting neighbors' wealth and initial inequality conditions on the dynamics of economic inequality and other outcomes. Ten actual rounds were implemented for each session. The number of rounds (i.e., 10) was fixed, but this was not told to the subjects in order to prevent end-game effects; instead, the game ended suddenly from the perspective of the players[5].

We manipulated two conditions across sessions: the level of economic inequality among the subjects in the initial round, and the visibility of connecting neighbors' wealth information (which was the same for all subjects in all rounds of a given session).

We prepared three levels of the initial economic inequality: "none" (Gini = 0.0), "low" (Gini = 0.2) and "high" (Gini = 0.4) **(Extended Data Table 1 and Extended Data Fig. 1)**. To experimentally generate different levels of economic inequality, and to quantify the amount of inequality in each group as the game progressed, we primarily used a *relative* inequality measure, namely, the Gini coefficient[6-8]. The Gini coefficient, which is a standard measure of inequality, is defined as "mean difference in wealth divided by twice the arithmetic mean" (following the scale invariance principle). This is in contrast to a "mean difference" measure (**Extended Data Fig. 5a)**, which is defined as "the average absolute difference in wealth between all pairs of individuals" (following the translation invariance principle), which we will return to below.

The Gini coefficient is given as:

$$\text{Gini} = (\Sigma\Sigma|x_i - x_j|)/2n^2\mu \,.$$

Here, the wealth of each subject is given by x, the size of the population is given by n (i and j range from 1 to n in each Σ), and μ is the mean wealth of the population.

These three different levels (Gini = 0.0, 0.2, and 0.4) were achieved by manipulating three parameters shaping the wealth distribution of subjects: the initial wealth of subjects in the rich group (r), the initial wealth of subjects in the poor group (p), and the fraction/probability of subjects being assigned to the rich group (f). Accordingly, we generated two groups of different initial wealth. The parameter settings stated below make the expected average initial wealth for each session 500 units regardless of the combination of (r, p, f).

First, when there was no initial economic inequality, (r, p, f) was set to be (500, 500, 0.5) **[Condition A]**, which meant that each subject had a 50% chance to be assigned to the "rich" group with an initial wealth of 500, and the other 50% chance to be assigned to a "poor" group with the initial wealth of 500. Obviously, in this setting, there was no difference between the "rich" and "poor" groups. This setting yielded the initial Gini coefficient of 0.0 and the initial mean difference of 0.

Second, when the level of initial economic inequality was low, (r, p, f) was set to be (700, 300, 0.5) **[Condition B]**, which meant that each subject had a 50% chance of being assigned to the rich group with an initial wealth of 700, and the other 50% were assigned to a poor group with the initial wealth of 300. For this low inequality condition, a second possibility was that (r, p, f) was set to be (850, 350, 0.3) **[Condition C]**, which meant that each subject had a 30% chance of being assigned to the rich group with an initial wealth of 850, and the other 70% were assigned to a poor group with the initial wealth of 350. These settings roughly generated the initial Gini coefficient of 0.2 (observed values ranged from 0.117 to 0.218) and an initial mean difference of 200 (observed values ranged from 98.7 to 250.0). Here, we generated two different wealth distributions because this would allow us to examine different combinations of wealth share and population share which achieved the same level of economic inequality (please see details in Section 2.3. and **Extended Data Table 1 and Extended Data Fig. 1**).

Third, when the level of initial economic inequality was high, the parameters (*r, p, f*) were set to be (1,150, 200, 0.3) **[Condition D]**, which meant that each subject had a 30% chance of being assigned to the rich group with an initial wealth of 1150, and the other 70% were assigned to a poor group with the initial wealth of 200. This setting roughly generated the initial Gini coefficient of 0.4 (observed values ranged from 0.347 to 0.411) and an initial mean difference of 399 (observed values ranged from 232.7 to 475.0).

Next, in a random half of the experimental sessions, subjects could see connecting neighbors' wealth information, i.e., when the setting was the "visible" condition (v =1). Even when the wealth of connected neighbors was visible, however, the subjects were not explicitly informed about who was assigned to which group (rich or poor) or explicitly informed of the existence of the two different initial wealth groups. Rather, in the "visible" condition, a subject could just see the amount of wealth of connected neighbors as well as his or her own wealth, and this information was updated at each round. In the "invisible" condition, a subject could see only his own wealth.

In the visible condition, as in the invisible condition, subjects were not shown their neighbors connections.

Since we performed ten sessions for each of four different wealth settings with two different visibility conditions, we performed a total of 80 sessions.

1.5. Implementations of actual rounds

Each subject was initially assigned to one location in an Erdos-Renyi random social network, with possible connections between each pair of subjects realized with a probability of 0.3 **(Fig. 1)**. Then, each subject was assigned at random to one of the two initial wealth levels (poor or rich) by a fixed probability (f = probability of 0.3 or 0.5 of being rich, depending on condition). Once each subject was assigned to be either poor or rich, each subject's initial wealth (starting units) was automatically fixed depending on the parameter setting (r and p), and was shown to the subject. Subjects were not informed about the overall wealth distribution.

Each round consisted of two steps: the cooperation step and the rewiring step (shown below). We repeated the cooperation step and the rewiring step ten times, and recorded the dynamics of the social networks.

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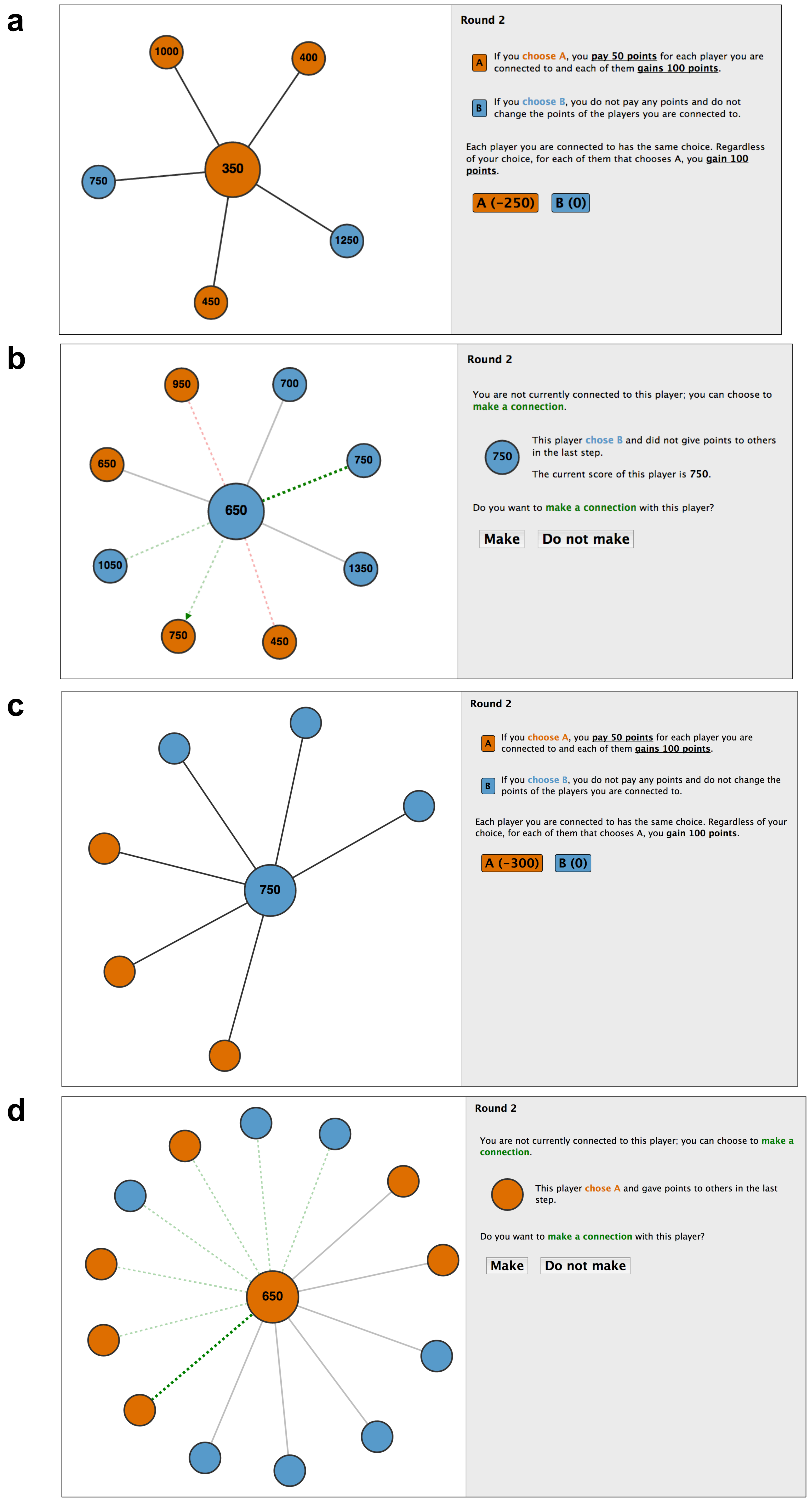

Screenshots of actual rounds. a – b, The screenshots for the “visible” condition are shown. **c – d,** The screenshots for the “invisible” condition are shown; the connecting neighbors’ wealth information is not available. Please refer to the explanation of the screenshots for practice rounds for details.

With respect to the cooperation step, each subject could choose to cooperate with connecting neighbors (paying 50 units multiplied by the number of connecting neighbors) or to defect against all of them (paying 0 units) at each round. Please note that subjects made a single choice with all their connecting neighbors. In a simplified example (the number of connecting neighbors is one), when one of the connecting neighbors of the focal subject chose to cooperate, the focal subject (as well as the other connecting neighbors of that neighbor) received 100 units by virtue of the neighbor's decision. When the neighbor chose to defect, the focal subject did not receive any units by virtue of the neighbor's decision. Thus, for each tie, the focal subject would earn either 100 units (defection towards cooperating neighbor), 50 units (both cooperation), 0 units (both defection), or –50 units (cooperation towards defecting neighbor) (**Extended Data Fig. 2**). Prior to making their decision in each round, subjects were shown their connecting neighbors' last move (cooperate or defect), except in the first round (where no previous moves existed). This was true in all conditions, regardless of the visibility of connecting neighbors' wealth information and wealth distributions. At the end of each turn, participants were informed about the decisions of their connecting neighbors in the round, and obtained their resulting payoff. *Negative values of wealth* at each round were allowed.

With respect to the rewiring step (after the cooperation step of each round of each session), 30% of all the possible pairs were chosen at random (rewiring rate = 0.3) (please refer to Section 1.6). If the chosen pair of subjects was currently connected, one of the two subjects was picked at random to be the decision-maker, and that subject decided whether or not to dissolve the tie (tie-breaking was unilateral). If the chosen pair was *not* currently connected, both subjects were asked if they wanted to form a tie; if both agreed, a tie was formed (tie-making was bilateral). The subjects were not informed of the rewiring rate of 0.3, which was held constant over the 10 rounds of all the 80 sessions.

At the beginning, subjects were connected to an average of 5.33 (SD = 0.98) neighbors across all the sessions (e.g., if there were initially exactly 17 individuals in a network, each individual had a 30% chance to be connected with each of 16 other individuals in the network; thus, the expected value of a subject's connected neighbors would be 4.8). The average subject was given the chance to form 2.41 new ties in an average round, and chose to do so 1.60 times on average (66.3%); the average subject was given the chance to break 1.22 ties in an average round, and chose to do so 0.27 times on average (22.4 %). Generally, consistent with past work[3,4], people preferred to cut ties to defectors and form ties to cooperators **(Supplementary Table 8)**.

1.6. Relationship with the previous experimental designs

Two previous studies by our team[3,4] provided the technical foundation of the present study. The purpose of those studies was to investigate the role of network fluidity in evolution of cooperation in humans (a topic not related to wealth inequality). These two studies used the same general experimental procedure as the present study: recruiting workers from Amazon Mechanical Turk (AMT) and letting them interact anonymously using our custom software ("Breadboard" – which is slated for open-source release) (please refer to Section 1.1). These two studies showed the dynamic social networks (intermediate fluidity) achieve a higher cooperation rate over time than fixed networks (no fluidity) or random networks (maximum fluidity). This is one of the reasons we permitted rewiring of ties in this experiment. The other reasons were that this is more realistic as a social process, and that we wanted affirmatively to measure the impact of wealth inequality on social tie formation (as a welfare outcome).

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It is known that the cooperation rate in repeated public goods game typically decays over time[3,4,9]. In static social networks with decaying cooperation, we would not fully observe the dynamics of wealth inequality, which is the main focus here. Most interactions would be in the right lower quadrant in **Extended Data Fig. 2**, where both an ego and an alter repeatedly choose D. Moreover, a certain level of network fluidity is typically observed in the modern human societies[10-12]. Therefore, we chose the rewiring rate of 0.3 for the present study, which was compatible with the rewiring rate maximizing cooperation rate in previous studies[3,4].

2. Statistical analysis

2.1. Summary statistics

A total of 1,462 subjects participated in our experiments. The average size of each session was 17.2 (IQR: 15.0 – 19.0), and 8.9% of the subjects dropped out during the actual rounds (we included them in the analyses). The average cooperation rate across the sessions was 61.5% (IQR: 47.3% – 77.9%); the average degree across the session was 8.19 (IQR: 6.50 – 9.65). These results were reflected in an average wealth of 1754.0 (IQR: 923.7 – 2409.0), average mean difference of 640.2 (IQR: 393.6 – 839.0), and average Gini coefficient of 0.205 (IQR: 0.137 – 0.258). The dynamics of each outcome variable from the 1st to 10th rounds are shown in **Fig. 2** (Gini coefficient) and **Fig. 3** (average wealth, cooperation rate, network degree, and transitivity [i.e. the probability that any two connecting neighbors of a focal subject connect with each other]). Network degree and transitivity are the two commonly used and simple measures to characterize network topology in network science.

We examined between-group differences at baseline using a *t* test **(Supplementary Table 1)**. The results show that none of the between-group comparisons (invisible v.s. visible, no initial inequality v.s. low initial inequality, no initial inequality v.s. high initial inequality, and low initial inequality v.s. high initial inequality) for the various measures, except initial observed Gini coefficient (which is our treatment assignment), are significantly different ($P > 0.05$). The *Standard Deviations* across the two groups are roughly similar by an F test ($P > 0.05$), except the No initial inequality v.s. High initial inequality comparison, with respect to the number of subjects at round 0 ($P = 0.038$).

Supplementary Table 1. Summary statistics at baseline at the session level (*N* = 80).

	Visible condition		Invisible condition		Visible v.s. Invisible
	Mean	SD	Mean	SD	*P*
Number of subjects at round 0 (subjects)	18.400	3.169	18.100	3.003	0.665
Initial observed Gini coefficient	0.192	0.142	0.191	0.142	0.965
Average initial wealth (units)	485.257	58.645	504.685	68.322	0.176
Average initial network degree (subjects)	5.443	0.917	5.214	1.034	0.298
Drop out over the rounds (subjects)	1.350	1.231	1.900	1.464	0.073

	No initial inequality		Low initial inequality		High initial inequality		None v.s. Low	None v.s. High	Low v.s. High
	Mean	SD	Mean	SD	Mean	SD	*P*	*P*	*P*
Number of subjects at round 0 (subjects)	18.050	3.649	18.650	3.134	17.650	2.231	0.534	0.679	0.161
Initial observed Gini coefficient	0.000	0.000	0.187	0.026	0.392	0.022	<0.001	<0.001	<0.001
Average initial wealth (units)	500.000	0.000	499.363	57.717	481.157	99.661	0.945	0.408	0.457
Average initial network degree (subjects)	5.260	1.092	5.442	0.987	5.170	0.850	0.533	0.773	0.274
Drop out over the rounds (subjects)	1.500	1.051	1.625	1.628	1.750	1.118	0.721	0.471	0.729

We displayed cumulative degree distributions for each of the six initial conditions, and used Kolmogorov-Smirnov test to compare them **(Extended Data Fig. 4)**; P-value correction due to multiple comparisons was not implemented here.

2.2. Analyses for session-level outcome variables

The main outcome variables of interest (degree of economic inequality [Gini coefficient], mean inter-individual difference in wealth [mean difference], average wealth, cooperation rate, average degree, and transitivity) are measured at the session level. Thus, we analyzed 880 session-rounds (80 sessions by 10 rounds/session + before the 1st round). Session-level results are shown in **Fig. 2, Fig. 3, and Extended Data Fig. 5a**. Since multiple observations from the same session can be correlated, and observations from multiple sessions in the same round can be correlated, our statistical analyses use multiway clustering of standard errors at the level of the session and the round in our regression models[13]. Technically, this multi-way clustering is a simple extension of one-way clustering, and enables us to take into account multiple dimensions at the same time. The programming codes are written by M.A. Petersen, available at: http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm.

We begin by examining treatment effects on the Gini coefficient **(Supplementary Table 2)**. We observe an overall significant positive effect of visibility on Gini, and of initial inequality on subsequent Gini **(col 1)**. We also observe a significant interaction between visibility and initial inequality when predicting Gini (P = 0.043) **(col 2)**. Therefore, we conduct decomposed analyses. Considering the effect of visibility by level of initial inequality, we find no significant effect of visibility in the no initial inequality condition **(col 3)**, but significant positive effects of visibility in the low initial inequality condition **(col 4)** and an even larger positive effect in the high initial inequality condition **(col 5)**. Considering the effect of initial inequality by visibility level, we see a significant effect in both the invisible condition **(col 6)** and the visible condition **(col 7)**, although the effect is more than twice as large in the visible condition. We also note that the relationship between initial inequality and Gini decays over time in the invisible condition, such that no significant relationship exists when examining just the second half of the game (rounds 6 – 10; coeff = 0.59, P = 0.259); whereas initial inequality still predicts Gini in the second half of the game in the visible condition (coeff = 0.297, P = 0.008).

Supplementary Table 2. Regressions predicting Gini at the session by round level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	Initial Gini=0.0	Initial Gini=0.2	Initial Gini=0.4	Invisible	Visible
Visible	0.0499***	0.00723	0.0185	0.0387**	0.104***		
	(0.0152)	(0.0220)	(0.0245)	(0.0189)	(0.0361)		
Initial Gini	0.286***	0.179**				0.179**	0.393***
	(0.0741)	(0.0753)				(0.0755)	(0.102)
Visible x InitGini		0.213**					
		(0.105)					
Constant	0.124***	0.145***	0.139***	0.187***	0.211***	0.145***	0.153***
	(0.0135)	(0.0124)	(0.0112)	(0.0144)	(0.0265)	(0.0124)	(0.0199)
Observations	800	800	200	400	200	400	400
Pseudo R-squared	0.268	0.295	0.023	0.075	0.202	0.115	0.308

Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$

Next, we consider the mean inter-individual difference (*mean difference*) in wealth **(Supplementary Table 3)**, rather than the Gini. The mean difference is defined as "the average absolute difference between all pairs of individuals" (following the *translation* invariance principle), while the Gini coefficient is defined as "mean difference divided by twice the arithmetic mean" (following the *scale* invariance principle)[6-8]. In other words, the Gini coefficient is a *relative* inequality measure, in which the influence of economic growth over time (or overall wealth) is controlled for, whereas the mean difference is an *absolute* inequality measure.

The mean difference measure can capture the change of economic variation in which, for example, two people's wealth changes from 1,150 and 200 (mean difference: 950) to 3,450 and 600 (mean difference: 2,850). On the other hand, in this example, the Gini coefficient cannot capture this change (in both circumstances, Gini = 0.35). This means the Gini coefficient can take economic growth and inflation over time into account.

Examining the mean difference, we observe no significant overall effects of visibility and a marginally significant positive effect of initial inequality **(col 1)**, but we do observe a highly significant interaction between the two (P = 0.005) **(col 2)**. Therefore, we again conduct decomposed analyses. Considering the effect of visibility by level of initial inequality, we find a significant negative effect of visibility in the no initial inequality condition **(col 3)**, no significant effects of visibility in the low initial inequality condition **(col 4)**, and a significant positive effect in the high initial inequality condition **(col 5)**. Considering the effect of initial inequality by visibility level, we see no significant effect in the invisible condition **(col 6)**, but a significant positive effect in the visible condition **(col 7)**.

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Supplementary Table 3. Regressions predicting mean difference at the session by round level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	Initial Gini=0.0	Initial Gini=0.2	Initial Gini=0.4	Invisible	Visible
visible	-2.096	-150.8***	-124.6**	-28.25	172.7**		
	(35.54)	(56.48)	(53.07)	(48.41)	(85.46)		
Initial Gini	488.2***	116.5				116.5	859.9***
	(135.9)	(177.8)				(178.7)	(186.9)
Visible x Initial Gini		743.4***					
		(266.0)					
Constant	588.9***	663.2***	627.8***	721.9***	674.4***	663.2***	512.5***
	(96.98)	(110.0)	(101.2)	(99.41)	(65.32)	(110.0)	(77.59)
Observations	800	800	200	400	200	400	400
Pseudo R-squared	0.045	0.070	0.044	0.002	0.075	0.002	0.141

Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$

Next, we consider average wealth, cooperation rate, degree, and transitivity **(Supplementary Table 4)**. For all four measures, we observe a significant negative relationship with visibility, no significant relationship with initial inequality, and no significant interaction between visibility and initial inequality. The only exception is a significant negative effect of initial inequality on wealth, but this effect is somewhat transient: when examining the second half of the game, there is no longer a significant relationship between initial equality and wealth (coeff = –926, P = 0.066; only a marginal trend) while visibility continues to have a strong significant negative effect on wealth (coeff = –816, P < 0.001).

This series of results **(Supplementary Tables 2, 3 and 4)** suggests that, in the No Initial Inequality condition, visibility decreases the level of average wealth; this decrease masks the positive effect of visibility on the reduction of economic inequality as measured by Gini coefficient (this is can be seen by examining the mean difference in subjects' wealth, defined as Gini coefficient multiplied by 2μ, rather than the Gini coefficient).

Supplementary Table 4. Regressions predicting average wealth, cooperation rate and degree at the session by round level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Average wealth		Cooperation rate		Degree		Transitivity	
Visible	-489.6***	-550.8***	-0.208***	-0.216***	-0.991**	-1.512**	-0.0962***	-0.0877***
	(149.7)	(187.8)	(0.0377)	(0.0515)	(0.392)	(0.608)	(0.0215)	(0.0260)
Initial Gini	-669.6**	-822.8**	-0.0835	-0.103	-1.713	-3.018	-0.0422	-0.0208
	(285.3)	(410.8)	(0.109)	(0.138)	(1.238)	(1.947)	(0.0547)	(0.0718)
Visible x Initial Gini		306.3		0.0384		2.609		-0.0428
		(543.4)		(0.210)		(2.425)		(0.109)
Constant	2,259***	2,289***	0.736***	0.740***	9.311***	9.572***	0.642***	0.638***
	(349.1)	(360.7)	(0.0309)	(0.0309)	(0.466)	(0.554)	(0.0362)	(0.0360)
Observations	800	800	800	800	800	800	800	800
Pseudo R-squared	0.065	0.065	0.228	0.228	0.073	0.081	0.132	0.133

Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$

For all the analyses in this section, we deal with initial Gini coefficient as a continuous variable (i.e. 0.0, 0.2, and 0.4) rather than as a categorical variable. Therefore, we test the linearity assumption (i.e. that the potential effect of low initial inequality [Gini = 0.2] on outcome measures is half of that of high initial inequality [Gini = 0.4], as compared to no initial inequality [Gini = 0.0]). Using regression models with the above-mentioned outcomes and with or without interaction terms, likelihood ratio tests that compared the model with a continuous initial Gini variable to that with two dummy variables (three categories, with No Initial Inequality as a reference category) generally show no substantial difference between these two models (all $P > 0.05$). The linearity assumption was also examined and confirmed for individual-level analyses.

Although we showed the session-level result of transitivity in **Fig. 3d**, the increase in transitivity could indeed be a byproduct of the increase in network degree across the rounds **(Fig. 3c)**. Therefore, we generated a random graph with the same network size and degree as those in the observed network at each round in each session, repeated the generation of a random graph 10,000 times, and took the mean of transitivity from the 10,000 graphs. The mean can be interpreted as the expected transitivity given a certain network size and degree, and the difference between the observed transitivity and the expected transitivity can be denoted as "excess transitivity adjusted for degree." The dynamics of excess transitivity **(Extended Data Fig. 5b)** implies that the difference in transitivity between the visible and the invisible conditions **(Fig. 3d)** can be explained by the difference in network degree **(Fig. 3c)**.

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We also examined how the prevalent cooperation rates of subjects might affect game outcomes, by evaluating how the (unconditional) cooperation rate at the first round in each session was associated with the Gini coefficient, average wealth, cooperation rate, and degree at the final round **(Extended Data Fig. 7)**. We show the aggregated relationship patterns with loess smoothed fit curves. Of course, the cooperation rate at the first round is also determined by the treatment variables of visibility and economic inequality conditions.

2.3. Comparison of the two conditions of low-level economic inequality

As described above, we included two different initial wealth distributions which both had Gini = 0.2 (low initial inequality, conditions B and C). The Gini coefficient uses a Lorenz curve to characterize the degree of economic inequality as the combination of the wealth share (y axis of the Lorenz curve) and the population share (x axis of the Lorenz curve) **(Extended Data Fig. 1)**. Since many combinations of the wealth and population shares can achieve the same amount of economic inequality (i.e., same Gini coefficient), we wanted to explore whether these distributional differences for a given Gini would affect our results. Hence, we used two different Gini = 0.2 conditions, such that our four conditions formed the four vertices of the square of condition A through D, as shown in **Extended Data Fig. 1**.

Here, we examine whether these two Gini = 0.2 conditions differed on any of our outcome variables **(Supplementary Table 5)**. To do so, we regress our five main outcome measures (Gini coefficient, mean difference, wealth, cooperation, and degree) against a binary indicator for condition B versus C, and a binary indicator for the "visible" condition. We find no significant effects of condition B vs C ($P > 0.3$ for all), and, in separate regressions, no significant interactions between condition B vs C and visibility ($P > 0.4$ for all). Therefore, these two initial settings of the low-level economic inequality do not seem to differ in any meaningful way, justifying our decisions to jointly analyze them as a single "Low Inequality" condition.

Supplementary Table 5. Regression analysis comparing Conditions B and C for all measures at the session by round level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Gini		Mean difference		Average wealth		Cooperation rate		Degree	
Visible	0.0387**	0.0333	-28.25	-43.09	-473.1***	-505.7**	-0.217***	-0.191***	0.0781	-0.299
	(0.0189)	(0.0278)	(48.37)	(74.45)	(177.2)	(206.2)	(0.0504)	(0.0610)	(0.619)	(0.811)
Condition C	0.00515	-0.000172	20.77	5.925	-47.14	-79.79	-0.0471	-0.0215	-1.390**	-1.767**
	(0.0188)	(0.0276)	(47.50)	(76.29)	(126.1)	(119.8)	(0.0455)	(0.0647)	(0.619)	(0.800)
Visible x Condition C		0.0106		29.69		65.31		-0.0512		0.754
		(0.0372)		(94.25)		(249.3)		(0.0902)		(1.236)
Constant	0.185***	0.187***	711.6***	719.0***	2,150***	2,167***	0.741***	0.728***	9.570***	9.758***
	(0.0197)	(0.0234)	(102.2)	(111.8)	(347.7)	(351.9)	(0.0383)	(0.0429)	(0.544)	(0.631)

Observations	400	400	400	400	400	400	400	400	200	200
Pseudo R-squared	0.076	0.077	0.003	0.003	0.052	0.053	0.247	0.250	0.107	0.115

Clustered standard errors in parentheses
*** P < 0.01, ** P < 0.05, * P < 0.1

2.4. Analyses for cooperation behaviors in the 1st round

To understand which behavioral mechanisms shape the outcomes that we found at the session level (see Section 2.2), we performed regression analyses with logit models of the individual-level data. We began by considering cooperation in the first round. Since there were no multiple observation over rounds (only first round is used in this case), our statistical analyses used clustering of standard errors at the level of the session.

For cooperation behaviors at the 1st round, we examined if the visibility of connecting neighbors' wealth information makes a difference in the subject's very first decision (prior to receiving any feedback about the behavior of others). Regressing cooperation on the visibility of connecting neighbors' wealth information shows that the "visible" condition is associated with lower initial cooperation probability (coeff = –0.318, P = 0.010) **(Supplementary Table 6, col 1: concise model)**.

Supplementary Table 6. Logit models predicting cooperation behaviors at the 1st round (n = 1,442 decisions).

	(1) All	(2) All	(3) Invisible Initial Gini = 0.0	(4) Invisible Initial Gini = 0.2	(5) Invisible Initial Gini = 0.4	(6) Visible Initial Gini = 0.0	(7) Visible Initial Gini = 0.2	(8) Visible Initial Gini = 0.4
Ego's degree		-0.133***	0.0262	-0.147***	-0.163*	-0.0806	-0.132***	-0.328***
		(0.0271)	(0.0725)	(0.0548)	(0.0916)	(0.0723)	(0.0452)	(0.103)
Ego's initial wealth (100-unit change)		0.0212		-0.0798	0.0327		0.0802	0.0525
		(0.0398)		(0.0684)	(0.0952)		(0.0898)	(0.0641)
Visibility	-0.318***	-0.938**						
	(0.123)	(0.450)						
Ego's initial wealth ≥ Connecting alters' average initial wealth or not, A		-0.590*		0.356	0.791		-0.0294	0.0429
		(0.333)		(0.366)	(0.592)		(0.391)	(0.440)
Visibility x A		0.479						
		(0.480)						
Initial Gini		-4.433***						
		(1.094)						
Visibility x Initial Gini		2.752*						
		(1.520)						
A x Initial Gini		3.440***						
		(1.091)						
A x Visibility x Initial Gini		-2.207						
		(1.622)						
Constant	0.924***	2.489***	1.165**	2.019***	0.856	1.229***	1.015**	1.928***
	(0.0955)	(0.398)	(0.460)	(0.376)	(0.553)	(0.417)	(0.424)	(0.604)

Observations	1,442	1,442	183	360	168	175	379	177

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$
Ego's degree represents the number of connecting neighbors of a focal ego; Ego's initial wealth ≥ Connecting alters' average initial wealth (or not) represents the variable of "social comparison."

We sought to understand why the visibility of the wealth information affects first period cooperation. One possibility is that visibility allows subjects to compare and judge the level of their wealth with reference to that of connecting neighbors' wealth. Therefore, we constructed models reflecting this possibility. We posit that, for both the "invisible" and "visible" conditions, each subject jointly uses the information at hand (i.e., the focal subject's degree, the focal subject's wealth) when the focal subject decides to cooperate or defect. And we posit that how they use this information varies by each of the six settings ("invisible" or "visible" combined with the three level of economic inequality). In addition, we posit that, only for the "visible" condition, each subject uses the information regarding whether the focal subject's wealth is larger or smaller than the average wealth of his connecting neighbors at the present round. Therefore, we create a simple dichotomous variable to represent whether the focal subject's wealth is larger than the average wealth of connecting neighbors, which we call the *variable of social comparison* (if ego's wealth is the same or larger than alters' average wealth at the round, the value of the variable of social comparison is 1; otherwise 0). We also perform further analyses by using alters' median wealth instead of alters' average wealth, which did not change the findings.

Here, we regressed cooperation (1: cooperate with connecting neighbors, 0: defect) on focal subject's initial wealth, focal subject's present wealth, focal subject's present degree, and the variable of social comparison, separately for each of the six settings ("invisible" or "visible" combined with the three levels of economic inequality). We included the variable of social comparison even in the "invisible" condition, so that the models for the "invisible" condition are the same as those for the "visible" conditions. We expected the coefficient for the variable of social comparison in the "invisible" condition to be non-significant, as this information is unobservable to the subjects (**Supplementary Tables 6, cols 3 – 8: stratified models)**. The model with the interaction term, which is not as parsimonious a model as the concise model, confirmed the findings from the stratified models (*P* for the *three-way interaction* term [visibility × initial Gini coefficient × variable of social comparison] = 0.174 – as further explained in Section 2.6) **(Supplementary Table 6, col 2: interaction model)**.

In sum, the results show that the variable of social comparison is not associated with first round cooperation in any of the six settings, which suggests that the visibility of connecting neighbors' wealth information decreases the level of subjects' cooperation overall, *regardless* of social comparison.

2.5. Analyses for cooperation behaviors at the 2nd – 10th rounds

At the 2nd-10th rounds, subjects can refer to past history of cooperation behaviors when they decide to cooperate or defect, which is a major difference from the 1st round. Therefore, we take into account focal subject's cooperation at the last round and the connecting neighbors' cooperation at the last round in the logit models. Furthermore, we again used multiway clustering of standard errors at the level of the session and the round in our regression models[13]. The results from the concise model shows that the "visible" condition was associated with lower cooperation probability (coeff = –0.366, $P < 0.001$) **(Supplementary Table 7, col1: concise model)**, and, therefore, we sought to understand whether the visibility of wealth information plays a role in the 2^{nd} – 10^{th} rounds.

Supplementary Table 7. Logit models predicting cooperation behaviors at the 2^{nd} to 10^{th} rounds (n = 12,110 decisions).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Invisible	Invisible	Invisible	Visible	Visible	Visible
			Initial	Initial	Initial	Initial	Initial	Initial
	All	All	Gini = 0.0	Gini = 0.2	Gini = 0.4	Gini = 0.0	Gini = 0.2	Gini = 0.4
Ego's degree		0.0737***	0.123***	0.0723**	0.208***	0.0635	0.0511*	-0.0114
		(0.0226)	(0.0382)	(0.0318)	(0.0617)	(0.0427)	(0.0282)	(0.0326)
Ego's initial wealth (100-unit change)		0.0473***		-0.00459	0.0610**		0.0516*	0.0775***
		(0.0176)		(0.0363)	(0.0300)		(0.0311)	(0.0234)
Ego's last wealth (100-unit change)		-0.0283***	-0.0351***	-0.0240***	-0.0451***	-0.0353***	-0.0259***	-0.0228***
		(0.00513)	(0.00538)	(0.00575)	(0.0142)	(0.00843)	(0.00459)	(0.00721)
Ego's last move, A	2.201***	0.977***	2.059	2.005***	0.160	0.786**	0.691***	1.157***
	(0.113)	(0.172)	(1.313)	(0.273)	(0.445)	(0.319)	(0.244)	(0.323)
Connecting alters' average last move (cooperation ≥ 0.50), B	1.447***	1.072***	0.937*	1.426***	0.538	1.578***	1.135***	1.220***
	(0.0944)	(0.178)	(0.536)	(0.301)	(0.373)	(0.249)	(0.129)	(0.349)
A x B		1.129***	0.627	0.611*	1.792***	0.941**	0.947***	0.618
		(0.167)	(1.428)	(0.345)	(0.544)	(0.381)	(0.213)	(0.466)
Visibility	-0.366***	-1.089***						
	(0.0752)	(0.228)						
Ego's last wealth ≥ Connecting alters' average last wealth or not, C		-0.622***	-0.250	-0.228*	0.105	0.370**	-0.100	-0.633***
		(0.226)	(0.311)	(0.122)	(0.200)	(0.168)	(0.0820)	(0.156)
Visibility x C		1.161***						
		(0.321)						
Initial Gini		-0.708						
		(0.716)						
Visibility x Initial Gini		2.258**						
		(0.920)						
C x Initial Gini		1.442*						
		(0.826)						

C x Visibility x Initial Gini		-3.929***						
		(1.381)						
Constant	-1.809***	-1.350***	-1.834***	-2.019***	-1.911***	-2.087***	-1.777***	-1.251***
	(0.166)	(0.277)	(0.586)	(0.487)	(0.491)	(0.232)	(0.309)	(0.317)
Observations	12,110	12,110	1,532	3,000	1,378	1,499	3,207	1,494

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$
Ego's degree represents the number of connecting neighbors of a focal ego; Ego's last wealth ≥ Connecting alters' average last wealth (or not) represents the variable of "social comparison."

For the stratified models, we included the same covariates as the models for the 1st round as well as focal subject's cooperation at the last round and the connecting neighbors' average cooperation at the last round, and the interaction term of the focal subject's and connecting neighbors' cooperation at the last round. We also created a dichotomous variable to represent whether the cooperation rate of all the connecting neighbors at the present round is more than 50% or not (if the percentage of connecting neighbors of a focal ego who are choosing cooperation is 50% or more, this variable is 1; otherwise 0).

The results show that, as the level of economic inequality increases (with the Gini coefficient going from 0.0 to 0.4), the effect of social comparison on cooperation changes from positive to negative (i.e. coeffs = 0.370, –0.100, and –0.633) **(Fig. 4 and Supplementary Table 7, cols 6 – 8: stratified model)** when the connecting neighbors' wealth information is available. However, this finding is not found when the connecting neighbors' wealth information is not available **(Fig. 4 and Supplementary Table 7, cols 3 – 5: stratified model)**. In the invisible condition **(Fig. 4, left)**, subjects who are poorer than their neighbors are as likely to cooperate as subjects who are richer than their neighbors (which is not surprising, since they are unaware of the wealth of their neighbors).

In order to formally test if the finding that the association between the variable of social comparison (the focal ego is richer) and cooperation decreases as the degree of initial economic inequality increases only in the "visible" condition, we construct a regression model using the all the subjects with the *three-way interaction* term (visibility × initial Gini coefficient × variable of social comparison). The P for the three-way interaction term is 0.002, which suggests that the phenomenon is observed only in the "visible" condition **(Supplementary Table 7, col 2: interaction model)**.

To extend this analysis, we performed the same analysis stratified by the last move of the focal individuals. The results show that the positive association of the variable of social comparison (the focal ego is richer) with cooperation in the No Initial Inequality setting in the visible condition is driven by previous cooperators **(Extended Data Fig. 6a)**. On the other hand, the negative association of the variable of social comparison (the focal ego is richer) with cooperation under the High Initial Inequality in the visible condition is driven by previous defectors **(Extended Data Fig. 6b)**.

2.6. Analyses for rewiring/social connection behavior

With respect to rewiring behavior, we examined if the visibility of connecting neighbors' wealth information made a difference in the subject's decision. In a multivariable logit model, we regressed the rewiring behavior (connect with the focal neighbor or not) on the visibility of connecting neighbors' wealth information controlling for the characteristic of the tie (new or existing tie), the focal individual's cooperation at the present round, and the focal neighbor's cooperation at the present round. The results show that the "visible" condition is not associated with becoming connected with a neighbor (coeff = –0.00427, $P = 0.960$), suggesting that the visibility of connecting neighbors' wealth information does *not* have a substantial influence on the subjects' rewiring behavior **(Supplementary Table 8)**. This conclusion is also supported from agent-based simulations (see Section 3).

Supplementary Table 8. Logit models predicting rewiring behaviors (n = 49,644 decisions).

	(1) All	(2) Existing ties	(3) New ties
Visibility	-0.00427	-0.0327	0.0225
	(0.0858)	(0.0869)	(0.0981)
Existing ties (Existing = 1, New = 0)	0.486***		
	(0.0764)		
Ego's last move	-0.829***	-0.872***	-0.866***
	(0.0935)	(0.0992)	(0.101)
Alter's last move	2.968***	3.621***	2.741***
	(0.109)	(0.179)	(0.0988)
Ego's initial wealth (100-unit change)	0.0131	-0.0200	0.0282*
	(0.0113)	(0.0152)	(0.0155)
Ego's last wealth (100-unit change)	0.00838*	0.0165***	0.00311
	(0.00454)	(0.00605)	(0.00487)
Constant	-0.375***	-0.0137	-0.287**
	(0.126)	(0.152)	(0.128)
Observations	49,644	16,700	32,944

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$

Indeed, **Fig. 3c** shows that subjects connect with a larger number of neighbors when the connecting neighbors' wealth information is available than when that is not available. However, the results from the regression models and agent-based simulations (see section 3) suggest that the difference in the degree between the visible and the invisible conditions can be simply explained by the difference in the cooperation rate. In more concrete terms, the invisible condition generally achieves a higher cooperation rate, and subjects are more likely to connect with subjects who cooperate at the last round, and, therefore, the invisible condition generally achieves higher degree, resulting in more dense social networks over the rounds.

2.7. The influence of rewiring behaviors on cooperation behaviors

Some subjects at a focal round choose to form a larger number of new ties or to break a larger number of existing ties, but others do not. Therefore, in this section, we examine the influence of forming/breaking ties in the t-th round on the cooperation behaviors at the t+1-th round. In more concrete terms, we additionally generated four variables: i) how many times a focal subject is asked to choose to make a new tie or not, in a focal round, ii) how often the focal subject chooses to "make" a new tie (proportion; ranging from 0 to 1), iii) how many times a focal subject is asked to choose to break an existing tie or not, at a focal round, and iv) how often the focal subject chooses to "cut" an existing tie (proportion; ranging from 0 to 1). When the variable i) or iii) is 0, we set the value for the variable ii) or iv) as 0, respectively. Then, we included these variables at the t-th round into the regression models to explain cooperation behaviors at the t+1-th round among the 2^{nd} to 10^{th} rounds. The results are shown in **Supplementary Table 9**. In sum, forming a larger number of new ties is associated with subjects being less likely to cooperate in the next round, while breaking a larger number of existing ties is associated with subjects being more likely to cooperate in the next round.

Supplementary Table 9. Additional analysis to explore the influence of rewiring behaviors on cooperation behaviors (n = 12,110 decisions).

	(1) Supplementary Table 7 (2)	(2) Variable added
Ego's degree	0.0737***	0.0872***
	(0.0226)	(0.0230)
Ego's initial wealth (100-unit change)	0.0473***	0.0591***
	(0.0176)	(0.0170)
Ego's last wealth (100-unit change)	-0.0283***	-0.0394***
	(0.00513)	(0.00583)
Ego's last move, A	0.977***	0.785***
	(0.172)	(0.176)
Connecting alters' average last move (Cooperation ≥ 0.50), B	1.072***	1.159***
	(0.178)	(0.195)
A x B	1.129***	1.130***
	(0.167)	(0.168)
Visibility	-1.089***	-1.178***
	(0.228)	(0.231)
Ego's last wealth ≥ connecting alters' average last wealth or not, C	-0.622***	-0.602**
	(0.226)	(0.242)
Visibility x C	1.161***	1.178***
	(0.321)	(0.318)
Initial Gini	-0.708	-0.782
	(0.716)	(0.743)
Visibility x Initial Gini	2.258**	2.356***
	(0.920)	(0.902)
C x Initial Gini	1.442*	1.458*
	(0.826)	(0.860)
C x Visibility x Initial Gini	-3.929***	-3.931***
	(1.381)	(1.344)
How many times ego is asked to make a new tie or not (variable i)		-0.0940***
		(0.0224)
How much percent ego chooses to "Make" in variable i (variable ii)		-0.859***
		(0.105)

How many times ego is asked to break an existing tie or not (variable iii)		0.0810**
		(0.0319)
How much percent ego chooses to “Cut” in variable iii (variable iv)		0.289**
		(0.116)
Constant	-1.350***	-0.634**
	(0.277)	(0.281)
Observations	12,110	12,110

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$
Ego’s degree represents the number of connecting neighbors of a focal ego; Ego's last wealth ≥ Connecting alters' average last wealth (or not) represents the variable of “social comparison.”

2.8. Analyses for initially rich and poor groups

We examine if subjects who are initially assigned to lower endowment (i.e. 200 units when Gini = 0.4, and 300 or 350 units when Gini = 0.2) can catch up with those who are initially assigned to higher endowment (i.e. 1,150 units when Gini = 0.4, and 700 or 850 units when Gini = 0.2).

Hence, we examined the dynamics of average wealth separately for the group of initially poor subjects and the group of initially rich subjects, with analytic procedures compatible with Figs. 2 and 3 **(Extended Data Fig. 3a and b)**. Moreover, we calculated standardized wealth at each session at each initial inequality and visibility setting, and traced the distribution of relative wealth between a group of initially poor subjects and a group of initially rich subjects **(Extended Data Fig. 3c – f)**.

3. Agent-Based Simulations

3.1. Agent-based models

The combination of richer subjects' cooperation with poorer subjects and poorer subjects' defection against richer subjects jointly decreases the level of economic inequality, while the combination of richer subjects' defection against poorer subjects and poorer subjects' cooperation with richer subjects jointly increases the level of economic inequality **(Extended Data Fig. 2)**. Therefore, the behavioral mechanism we report based on the analyses at the individual level (Section 2.5) can intuitively explain the session-level dynamics of the degree of economic inequality. We perform agent-based simulations to confirm that the comparison of the wealth of the focal individual and the average wealth of connecting neighbors is a sufficient variable to explain the difference between the consequences in the "visible" condition and those in the "invisible" condition across the different levels of initial economic inequality.

We prepared for the same number of rounds (10 rounds) for each session (iteration). We use a random network structure to allocate agents, where 30% of all the possible dyads are connected (the initial network structure varies at each session). We also use the same rewiring rate (0.3). As for the settings of agents, we prepared for 17 individuals, which is the median of the subjects in our experiments, for all the sessions. In order to minimize the influence of noise, we set the drop-out rate during a single session to be zero.

As for the settings of agent behaviors, we aimed to construct a parsimonious model to determine them. Although we included several control variables in the regression models for the experiments (e.g., degree) to control for the potential confounding (see Section 2), such full models will end in over-fitting in agent-based models. Therefore, we constructed theory-based models with a smaller number of independent variables. For a model for the situation where alters' wealth information is private, we posit that the present move (cooperation) is determined only by the focal subject's last move. On the other hand, for a model of the situation where alters' wealth information is public, we added three variables: (a) a dichotomous variable representing if the present wealth of an ego is larger than the average wealth of the alters or not, (b) the initial level of wealth inequality (0, 0.2 or 0.4), and (c) an interaction term between the dichotomous variable and the continuous variable of wealth inequality. Each parameter is calculated from the regression analyses. The details of our models for the agent-based simulations are stated as follows.

First, the cooperation behavior at the 1st round is determined by nothing in the "invisible" condition (i.e. constant) **(Supplementary Table 10, col 1)** and by a continuous variable of the initial economic inequality (0, 0.2, and 0.4) at the "visible" condition **(Supplementary Table 10, col 2)**. Second, the cooperation behavior at the 2nd – 10th rounds is determined by the focal individual's cooperation at the last round in the "invisible" condition **(Supplementary Table 10, cols 3 and 4)** and by the focal individual's cooperation at the last round, the initial Gini coefficient, whether or not the present wealth of the focal individual is larger than the average wealth of the connecting neighbors (1 for yes, and 0 for no), and an interaction term (product of the latter two terms) in the "visible" condition **(Supplementary Table 10, cols 5 and 6)**. This reflects the behavioral mechanism hypothesized by the results of the experiments. Third, the rewiring behavior is determined by the characteristic of the tie (new or existing tie), the focal individual's cooperation at the present round, and the focal neighbor's cooperation at the present round in both the "invisible" and “visible” conditions **(Supplementary Table 11)**.

Supplementary Table 10. Parameters for cooperation behaviors used in the agent-based simulations, which were obtained from parsimonious logit models.

	(1) Round 1 Invisible	(2) Round 1 Visible	(3) Rounds 2-10 Invisible Defection at last move	(4) Rounds 2-10 Invisible Cooperation at last move	(5) Rounds 2-10 Visible Defection at last move	(6) Rounds 2-10 Visible Cooperation at last move
Ego's last wealth ≥ Connecting alters' average last wealth or not, C					0.257	0.620**
					(0.258)	(0.279)
Initial Gini		-1.017*			1.294***	0.422
		(0.544)			(0.378)	(0.583)
C x Initial Gini					-2.508***	-1.170
					(0.931)	(1.120)
Constant	0.924***	0.813***	-1.040***	2.062***	-1.232***	0.737***
	(0.0961)	(0.134)	(0.192)	(0.119)	(0.142)	(0.167)
Observations	711	731	1,612	4,298	2,888	3,312

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$
Ego's last wealth ≥ Connecting alters' average last wealth (or not) represents the variable of “social comparison.”

Supplementary Table 11. Parameters for rewiring behaviors used in the agent-based simulations, which were obtained from parsimonious logit models.

	(1) All
Existing ties (Existing = 1, New = 0)	0.513***
	(0.0758)
Ego's last move	-0.852***
	(0.0959)
Alter's last move	2.965***
	(0.106)
Constant	-0.181***
	(0.0698)
Observations	49,644

Beta coefficients of logit models are reported. Clustered standard errors in parentheses
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$

In this setting, we assume agents in the “invisible” condition cannot use any information on wealth, while those in the “visible” condition do use the information on wealth, in order to gain an understanding of the level of initial economic inequality and to examine whether or not they are better off than connecting neighbors. All the parameters involved are obtained from logit models using the data of the experiment **(Supplementary Tables 10 and 11)**. Since we are interested in the influence of the initial economic inequality, we do not allow these agent behaviors to evolve over the ten rounds (no social learning during the session).

We prepared for the same eight settings as the experiments (two for the wealth information availability ("invisible", "visible") conditions by four wealth distributions (conditions A – D). We performed the simulations 1,000 times for each setting (a total of 8,000 iterations). For details, please refer to the R code for the agent-based simulations (Section 3.3). The main results of the agent-based simulations are shown in **Extended Data Fig. 8**, where we show the agent-based simulations roughly reproduce the results from the experiments.

Since we did not allow agents to drop out in the simulations, the simulation results also suggest that the potential influence of drop outs for the entire analysis is likely small.

3.2. Robustness check of our experimental setting

In the 80 session of our experiment, we terminated each session (suddenly) at the tenth round, and we always applied the same rules for rewiring behaviors. Since we did not tell subjects at which round a session would finish, it is possible for us to simulate and predict the influence of changing the round length with agent-based models. Using the estimated parameters from the implemented 10-round experiments, we simulated the Gini coefficient and other dynamics up to 20 rounds. Results show that a substantial effect of visibility on Gini coefficient, especially when initial Gini = 0.2 and 0.4, is indeed stably observed up to Round 20 **(Extended Data Fig. 9)**. Thus, our simulations suggest that our results are robust to running the experiments for a longer time.

3.3. R code for simulations

```
# Agent-based modeling for the inequality experiment

#####################################################
# Section 1. NOTES, packages, and Parameters
#Importing libary
suppressMessages(library(igraph)) # for network graphing
suppressMessages(library(reldist)) # for gini calculation
suppressMessages(library(boot)) # for inv.logit calculation
#Two prefixed functions
#rank
rank1 = function(x) {rank(x,na.last=NA,ties.method="average")[1]} #a smaller value has a smaller rank.

#gini mean difference (a.k.a. mean difference: please refer to https://stat.ethz.ch/pipermail/r-help/2003-April/032782.html)
gmd = function(x) {
    x1 = na.omit(x)
       n = length(x1)
 tmp = 0
    for (i in 1:n) {
       for (j in 1:n) {
          tmp <- tmp + abs(x1[i]-x1[j])
       }
    }
 answer = tmp/(n*n)
    return(answer)
 }

# List of manipulating parameters of experiments
#L : number of round
#V : Visible or not
#A : Income of a rich-group subject
#B : Income of a poor-group subject
#R : Probability to be assigned to a rich group
#I : Number of the same-parameter trial

#Example
L = 10
```

```
V = 0
A = 700
B = 300
R = 0.5
I = 0

# List of fixed parameters of experiments (assumptions)
#Rewiring rate = 0.3

#GINI coefficient (can be known by A or B)
GINI = 0*as.numeric(A==500) + 0.2*as.numeric(A %in% c(700,850)) + 0.4*as.numeric(A ==1150)

#Collecting data frame (final output data frame)
result =
 data.frame(round=0:L,n_par=NA,n_A=NA,avg_coop=NA,avg_degree=NA,avg_wealth=NA,gini=NA,gmd=NA,avg_coop_A=NA,avg_degree_A=NA,avg_wealth_
 A=NA,gini_A=NA,gmd_A=NA,avg_coop_B=NA,avg_degree_B=NA,avg_wealth_B=NA,gini_B=NA,gmd_B=NA)
#_A is for a richer group and _B is for a poorer group

####################################################
# Section 2: Round 0 (Agents and environments)
#Node data generation
N = 17 # median of the number of participants over rounds.
node_r0 = data.frame(ego_id=1:N, round=0)
node_r0$group = sample(c("rich","poor"),N,replace=TRUE,prob=c(R,1-R)) #R is defined as the probability to be assigned to the rich
 group
node_r0$initial_wealth = ifelse(node_r0$group=="rich",A,B)

#Link data generation
ego_list = NULL
for (i in 1:N) { ego_list = c(ego_list,rep(i,N)) }
link_r0 = data.frame(ego_id=ego_list,alt_id=rep(1:N,N))
link_r0 = link_r0[(link_r0$ego_id < link_r0$alt_id),] #The link was bidirectional, and thus the half and self are omitted.
link_r0$connected = sample(0:1,dim(link_r0)[1],replace=TRUE,prob=c(0.7,0.3)) #Initial rewiring rate is fixed, 0.3

link_r0c_ego = link_r0[link_r0$connected==1,]
link_r0c_alt = link_r0[link_r0$connected==1,]
colnames(link_r0c_alt) = c("alt_id","ego_id","connected")
link_r0c = rbind(link_r0c_ego,link_r0c_alt) #this is bidirectional (double counted) for connected ties.

link_r0c = link_r0c[order(link_r0c$ego_id),]
link_r0c$alternumber = NA #putting the number for each alter in the same ego
link_r0c[1,]$alternumber = 1
for (i in 1:(dim(link_r0c)[1]-1))
 {
 if (link_r0c[i,]$ego_id == link_r0c[i+1,]$ego_id)
        {
        link_r0c[i+1,]$alternumber = link_r0c[i,]$alternumber + 1
        }
 else
        {
        link_r0c[i+1,]$alternumber = 1
        }
 #print(i)
 }
link_r0c2 = reshape(link_r0c, direction = "wide", idvar=c("ego_id","connected"), timevar="alternumber")
link_r0c2$initial_degree = apply(link_r0c2[,colnames(link_r0c2)[substr(colnames(link_r0c2),1,6) == "alt_id"]],1,function(x)
 {length(na.omit(x))}) #Degree of each ego
link_r0c2[is.na(link_r0c2$initial_degree)==1,"initial_degree"] = 0

#Reflect the degree and initial local gini coefficient into the node data
node_r0 = merge(x=node_r0,y=link_r0c2,all.x=TRUE,all.y=FALSE,by="ego_id")

node_r0$initial_avg_env_wealth = NA
node_r0$initial_local_gini = NA #local gini coefficient of the ego and connecting alters
node_r0$initial_rel_rank = NA #local rank of ego among the ego and connecting alters (divided by the number of the go and connecting
 alters)
for (i in 1:(dim(node_r0)[1]))
 {
 node_r0[i,]$initial_avg_env_wealth = mean(na.omit(node_r0[node_r0$ego_id %in%
 node_r0[i,colnames(node_r0)[substr(colnames(node_r0),1,6) %in% c("ego_id","alt_id")]],"initial_wealth"]))
 node_r0[i,]$initial_local_gini = gini(na.omit(node_r0[node_r0$ego_id %in% node_r0[i,colnames(node_r0)[substr(colnames(node_r0),1,6)
 %in% c("ego_id","alt_id")]],"initial_wealth"]))
 node_r0[i,]$initial_rel_rank = rank1(na.omit(node_r0[node_r0$ego_id %in% node_r0[i,colnames(node_r0)[substr(colnames(node_r0),1,6)
 %in% c("ego_id","alt_id")]],"initial_wealth"]))/length(na.omit(node_r0[node_r0$ego_id %in%
 node_r0[i,colnames(node_r0)[substr(colnames(node_r0),1,6) %in% c("ego_id","alt_id")]],"initial_wealth"]))
 }

#Finalization of round 0 and Visualization
#plot(graph.data.frame(link_r0[link_r0$connected==1,],directed=F)) #plot.igraph
result[result$round==0,2:18] =
 c(length(node_r0$ego_id),length(node_r0[node_r0$group=="rich",]$ego_id),NA,mean(node_r0$initial_degree),mean(node_r0$initial_wealth),
```

```
 gini(node_r0$initial_wealth),gmd(node_r0$initial_wealth),NA,mean(node_r0[node_r0$group=="rich",]$initial_degree),mean(node_r0[node_r0
 $group=="rich",]$initial_wealth),gini(node_r0[node_r0$group=="rich",]$initial_wealth),gmd(node_r0[node_r0$group=="rich",]$initial_wea
 lth),NA,mean(node_r0[node_r0$group=="poor",]$initial_degree),mean(node_r0[node_r0$group=="poor",]$initial_wealth),gini(node_r0[node_r
 0$group=="poor",]$initial_wealth),gmd(node_r0[node_r0$group=="poor",]$initial_wealth))

#For the loop at the next round (for round 1, the initial one is the same as the previous [1 prior] one)
node_import = node_r0
node_import$initial_coop = NA
node_import$prev_coop = NA
node_import$prev_wealth = node_import$initial_wealth
node_import$prev_degree = node_import$initial_degree
node_import$prev_avg_env_wealth = node_import$initial_avg_env_wealth
node_import$prev_local_gini = node_import$initial_local_gini
node_import$prev_rel_rank = node_import$initial_rel_rank
node_import$prev_local_rate_coop = NA

link_import = link_r0

#####################################################
# Section 3: Rounds 1 to 10 or more (behaviors in simulation: the equation of cooperation is different at round 1 because of no
 history)
#3-1: Cooperation phase
for (k in 1:L)
{
node_rX = node_import #Importing data
node_rX$round = node_rX$round + 1

node_rX[is.na(node_rX$prev_degree)==1,"prev_degree"] = 0
node_rX[is.na(node_rX$prev_local_rate_coop)==1,"prev_local_rate_coop"] = 0

#Only this calculation needs to change from Round 1
if (k==1) {
 node_rX$prob_coop = as.numeric(V==0)*inv.logit(0.9241803) +
                                     as.numeric(V==1)*inv.logit((-1.017021)*GINI + (0.8130213))
 } else {
 node_rX$prob_coop = as.numeric(V==0 & node_rX$prev_coop==0)*inv.logit(-1.039916) +
                                     as.numeric(V==0 & node_rX$prev_coop==1)*inv.logit(2.062023) +
                                     as.numeric(V==1                      &                      node_rX$prev_coop==0)*inv.logit((-
 0.2574838)*as.numeric(node_rX$prev_avg_env_wealth      -      node_rX$prev_wealth      >      0)      +      (-1.214198)*GINI      +
 (2.508148)*GINI*as.numeric(node_rX$prev_avg_env_wealth - node_rX$prev_wealth > 0) + (-0.9749075)) +
                                     as.numeric(V==1                      &                      node_rX$prev_coop==1)*inv.logit((-
 0.6197254)*as.numeric(node_rX$prev_avg_env_wealth      -      node_rX$prev_wealth      >      0)      +      (-0.7480261)*GINI      +
 (1.169674)*GINI*as.numeric(node_rX$prev_avg_env_wealth - node_rX$prev_wealth > 0) + (1.356784))
 }

node_rX$coop = apply(data.frame(node_rX$prob_coop),1,function(x) {sample(1:0,1,prob=c(x,(1-x)))})

if (k==1) {
 node_rX$initial_coop = node_rX$coop
 } else {
 node_rX$initial_coop = node_rX$initial_coop
}

node_rX$cost = (-50)*node_rX$coop*node_rX$prev_degree
node_rX$n_coop_received = NA
for (i in 1:(dim(node_rX)[1]))
 {
 node_rX[i,]$n_coop_received   =   sum(node_rX[node_rX$ego_id   %in%   node_rX[i,colnames(node_rX)[substr(colnames(node_rX),1,6)   ==
 "alt_id"]],"coop"])
 }
node_rX$benefit = 100*node_rX$n_coop_received
node_rX$payoff = node_rX$cost + node_rX$benefit
node_rX$wealth = node_rX$prev_wealth + node_rX$payoff
node_rX$rel_rank = NA
node_rX$local_rate_coop = NA
for (i in 1:dim(node_rX)[1])
 {
 node_rX[i,]$rel_rank  =  rank1(na.omit(node_rX[node_rX$ego_id  %in%  node_rX[i,colnames(node_rX)[substr(colnames(node_rX),1,6)  %in%
 c("ego_id","alt_id")]],"wealth"]))/length(na.omit(node_rX[node_rX$ego_id                                                     %in%
 node_rX[i,colnames(node_rX)[substr(colnames(node_rX),1,6) %in% c("ego_id","alt_id")]],"wealth"]))
 node_rX[i,]$local_rate_coop = mean(na.omit(node_rX[node_rX$ego_id %in% node_rX[i,colnames(node_rX)[substr(colnames(node_rX),1,6) %in%
 c("ego_id","alt_id")]],"coop"]))
 }
node_rX$growth = as.numeric((node_rX$wealth/node_rX$prev_wealth) > 1)

node_rX                                                                                                                            =
 node_rX[,c("ego_id","round","group","prev_degree","initial_wealth","initial_local_gini","initial_coop","coop","wealth","rel_rank","lo
 cal_rate_coop","growth")] #Pruning the previous-round data (degree is not updating yet)

#3-2: Rewiring phase
# 30% of ties (unidirectional) are being rewired
```

```
link_rX_1 = link_import #Importing data (bidirectioanl ego-alter [ego_id < alter_id])
colnames(link_rX_1) = c("ego_id","alt_id","prev_connected")
link_rX_1$challenge = sample(0:1,dim(link_rX_1)[1],replace=TRUE,prob=c(0.7,0.3)) # The bidirectional ties being rewired are selected (rewiring rate = 0.3).

ego_node_data = node_rX[,c("ego_id","wealth","coop","prev_degree","initial_wealth","initial_local_gini","initial_coop","rel_rank","local_rate_coop","growth")]
colnames(ego_node_data) = c("ego_id","ego_wealth","ego_coop","ego_prev_degree","ego_initial_wealth","ego_initial_local_gini","ego_initial_coop","ego_rel_rank","ego_local_rate_coop","ego_growth")
alt_node_data = node_rX[,c("ego_id","wealth","coop","prev_degree","initial_wealth","initial_local_gini","initial_coop","rel_rank","local_rate_coop","growth")]
colnames(alt_node_data) = c("alt_id","alt_wealth","alt_coop","alt_prev_degree","alt_initial_wealth","alt_initial_local_gini","alt_initial_coop","alt_rel_rank","alt_local_rate_coop","alt_growth")

link_rX_2 = merge(x=link_rX_1,y=ego_node_data,all.x=TRUE,all.y=FALSE,by="ego_id")
link_rX_3 = merge(x=link_rX_2,y=alt_node_data,all.x=TRUE,all.y=FALSE,by="alt_id")
link_rX_3$choice = sample(c("ego","alt"),dim(link_rX_3)[1],replace=TRUE,prob=c(0.5,0.5)) #decision maker for breaking a link, which is an unilateral decision

#ego_prob: probability of choosing to connect when challenged (asked)
link_rX_3$ego_prob = inv.logit((0.5134401)*link_rX_3$prev_connected + (-0.852406)*link_rX_3$ego_coop + (2.96549)*link_rX_3$alt_coop + (-0.1808545))
link_rX_3$alt_prob = inv.logit((0.5134401)*link_rX_3$prev_connected + (-0.852406)*link_rX_3$alt_coop + (2.96549)*link_rX_3$ego_coop + (-0.1808545))

link_rX_3$prob_connect = ifelse(link_rX_3$prev_connected == 1, ifelse(link_rX_3$choice == "ego", link_rX_3$ego_prob, link_rX_3$alt_prob), link_rX_3$ego_prob*link_rX_3$alt_prob)

link_rX_3$connect_update = apply(data.frame(link_rX_3$prob_connect),1, function(x) {sample(1:0,1,prob=c(x,(1-x)))})
link_rX_3$connected = ifelse(link_rX_3$challenge==0,link_rX_3$prev_connected,link_rX_3$connect_update)
link_rX = link_rX_3[,c("ego_id","alt_id","connected")] #pruning and data is updated

#Reflect the degree and local gini coefficient into the node data
link_rXc_ego = link_rX[link_rX$connected==1,]
link_rXc_alt = link_rX[link_rX$connected==1,]
colnames(link_rXc_alt) = c("alt_id","ego_id","connected")
link_rXc = rbind(link_rXc_ego,link_rXc_alt)
link_rXc = link_rXc[order(link_rXc$ego_id),]
link_rXc$alternumber = NA
link_rXc[1,]$alternumber = 1
for (i in 1:(dim(link_rXc)[1]-1))
 {
 if (link_rXc[i,]$ego_id == link_rXc[i+1,]$ego_id)
        {
        link_rXc[i+1,]$alternumber = link_rXc[i,]$alternumber + 1
        }
 else
        {
        link_rXc[i+1,]$alternumber = 1
        }
 #print(i)
 }
link_rXc2 = reshape(link_rXc, direction = "wide", idvar=c("ego_id","connected"), timevar="alternumber")
link_rXc2$degree = apply(link_rXc2[,colnames(link_rXc2)[substr(colnames(link_rXc2),1,3) == "alt"]],1,function(x) {length(na.omit(x))})

node_rX_final = merge(x=node_rX[,c("ego_id","round","group","initial_wealth","initial_local_gini","initial_coop","coop","wealth","growth")],y=link_rXc2,all.x=TRUE,all.y=FALSE,by="ego_id")
node_rX_final[is.na(node_rX_final$degree)==1,"degree"] = 0

node_rX_final$avg_env_wealth = NA
node_rX_final$local_gini = NA #needs to be updated because the social network changes at the rewiring phase
node_rX_final$local_rate_coop = NA
node_rX_final$rel_rank = NA
for (i in 1:dim(node_rX_final)[1])
 {
 node_rX_final[i,]$avg_env_wealth = mean(na.omit(node_rX_final[node_rX_final$ego_id %in% node_rX_final[i,colnames(node_rX_final)[substr(colnames(node_rX_final),1,6) %in% c("ego_id","alt_id")]],"wealth"]))
 node_rX_final[i,]$local_gini = gini(na.omit(node_rX_final[node_rX_final$ego_id %in% node_rX_final[i,colnames(node_rX_final)[substr(colnames(node_rX_final),1,6) %in% c("ego_id","alt_id")]],"wealth"]))
 node_rX_final[i,]$local_rate_coop = mean(na.omit(node_rX_final[node_rX_final$ego_id %in% node_rX_final[i,colnames(node_rX_final)[substr(colnames(node_rX_final),1,6) %in% c("ego_id","alt_id")]],"coop"]))
 node_rX_final[i,]$rel_rank = rank1(na.omit(node_rX_final[node_rX_final$ego_id %in% node_rX_final[i,colnames(node_rX_final)[substr(colnames(node_rX_final),1,6) %in% c("ego_id","alt_id")]],"wealth"]))/length(na.omit(node_rX_final[node_rX_final$ego_id %in% node_rX_final[i,colnames(node_rX_final)[substr(colnames(node_rX_final),1,6) %in% c("ego_id","alt_id")]],"wealth"]))
 }
```

```
#Finalization of round X and Visualization
#plot(graph.data.frame(link_rX[link_rX$connected==1,],directed=F)) #plot.igraph
result[result$round==k,2:18] =
 c(length(node_rX_final$ego_id),length(node_rX_final[node_rX_final$group=="rich",]$ego_id),mean(node_rX_final$coop),mean(node_rX_final
 $degree),mean(node_rX_final$wealth),gini(node_rX_final$wealth),gmd(node_rX_final$wealth),mean(node_rX_final[node_rX_final$group=="ric
 h",]$coop),mean(node_rX_final[node_rX_final$group=="rich",]$degree),mean(node_rX_final[node_rX_final$group=="rich",]$wealth),gini(nod
 e_rX_final[node_rX_final$group=="rich",]$wealth),gmd(node_rX_final[node_rX_final$group=="rich",]$wealth),mean(node_rX_final[node_rX_f
 inal$group=="poor",]$coop),mean(node_rX_final[node_rX_final$group=="poor",]$degree),mean(node_rX_final[node_rX_final$group=="poor",]$
 wealth),gini(node_rX_final[node_rX_final$group=="poor",]$wealth),gmd(node_rX_final[node_rX_final$group=="poor",]$wealth))

#For the loop
node_import = node_rX_final
colnames(node_import)[colnames(node_import) %in%
 c("coop","wealth","growth","degree","avg_env_wealth","local_gini","local_rate_coop","rel_rank")] =
 c("prev_coop","prev_wealth","prev_growth","prev_degree","prev_avg_env_wealth","prev_local_gini","prev_local_rate_coop","prev_rel_rank
 ")
link_import = link_rX

#print(paste0("Round ",k," is done."))
}

print(result)
```

3.4. Replication of the agent-based simulations

AN wrote the R codes shown in Section 3.3. HS wrote the equivalent codes using Python 2.75, which extracted the same results shown in **Extended Data Figs. 8 and 9** (not shown).

4. Video for network dynamics illustration

To illustrate the dynamics of inequality, wealth, cooperation, and interconnectedness (degree) in the present experiments, we created a video file of selected sessions **(Supplementary Video 1)**.

5. Code and data availability

The programming code as well as the experimental data are stored and available upon request at Yale Institute for Network Science Data Archive.

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