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The concomitance of prosociality and social networking agency

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Abstract

The awareness of individuals regarding their social network surroundings and their capacity to use social connections to their advantage are well-established human characteristics. Economic games, incorporated with network science, are frequently used to examine social behaviour. Traditionally, such game models and experiments artificially limit players' abilities to take varied actions toward distinct social neighbours (i.e., to operate their social networks). We designed an experimental paradigm that alters the degree of social network agency to interact with individual neighbours, and applied it to the prisoner's dilemma (N = 735), trust game (N = 735), and ultimatum game (N = 735) to investigate cooperation, trust, and fairness. The freedom to interact led to more prosocial behaviour across all three economic games and resulted in higher wealth and lower inequality compared to controls without such freedom. These findings suggest that human behaviour is more prosocial than current science indicates.

Keywords: behavioural science, networks, cooperation, prosociality

Social networks coordinate society. They embody an evolved cognizance of social surroundings and the capacity to use these networks advantageously [1, 2]. Intrinsically linked to social networks is another fundamental societal feature—cooperation. The maintenance of social networks is a cooperative act, and conversely, without social networks, cooperation would not exist at the scale and complexity observed even in simple societies [3]. Consequently, any explanation of these foundational cultural elements must encompass both. However, the majority of studies investigating the origins of cooperation overlook the capacity of humans to actively manage their social networks—their social networking agency [4–6]. Similarly, studies examining how individuals use their social networks seldom explore the evolutionary roots predating the demographic transition [3]. The burgeoning field of studying cooperation in populations structured by social networks can be categorized into four areas. First, a line of research originating from theoretical population biology [6], primarily aimed at reconciling the cost of prosociality with its emergence in prehistoric societies, occasionally uses social network structure as a contextual backdrop for the decisions of rational agents [7–9]. Second, there is a sustained interest in how network structure and evolutionary game dynamics can collectively generate complex patterns [10]. Third, anthropologists have a longstanding tradition of documenting networks of gift-giving, food-sharing, and other elements of cooperative community building [11]. A fourth area combines networks and cooperative decisions in studies of optimal network formation in economic game theory [12]. Despite the diversity of these efforts, a fundamental question persists: How does the ability to actively use one's social network influence cooperation?

Using one's social network necessitates the freedom to behave differently towards various individuals in one's social environment. Indeed, in the game-theoretic study of cooperation, any restriction on this freedom would stem from social conventions that form part of the dilemma under investigation. Thus, in our study, we bridge the gap in the literature by modulating between situations that retain this basic freedom and the artificially constrained setup of players interacting uniformly with their entire neighbourhood, which has become the conventional approach.

We present the results of 15 experimental setups and reveal that the ability to act differently towards individual neighbours universally enhances cooperation, trust, and fairness, leading to higher payoffs and reduced inequality. Additionally, we identified three distinct behavioural phenotypes for players in each game and demonstrated how the distribution of these phenotypes shifts as the ability to exploit their social network increases in the population. Finally, we developed numerical models for each type of game to provide a deeper understanding of our observed experimental results.

Laboratory experiments

We employed repeated spatial versions of three economic games—the prisoner's dilemma, the trust game, and the ultimatum game—to examine cooperation, trust, and fairness. These games were chosen due to their extensive use in prosocial behaviour research [13, 14]. The classical prisoner's dilemma involves two players who simultaneously decide between cooperation and defection. If one player defects while the other cooperates, the defector gains more than if both had cooperated. Consequently, defection becomes a rational, self-regarding solution, leading to a Nash equilibrium where both players defect and earn less than if they had cooperated [15].

Unlike the prisoner's dilemma, the standard trust and ultimatum games proceed sequentially over two stages [14]. In the trust game, a trustor can share an endowment with a trustee. The entrusted amount is typically tripled, and the trustee then decides how much to return. Self-interest dictates that the trustor should send nothing and the trustee should return nothing [16].

The ultimatum game involves a proposer dividing an endowment and a responder accepting or rejecting the division. If accepted, the division proceeds; if rejected, neither player receives anything. A self-regarding proposer offers the minimum, and a self-regarding responder accepts it [17].

Contrary to theoretical predictions, experiments reveal more prosocial human behaviour. For instance, in one-shot games, players cooperate approximately half of the time in the prisoner's dilemma, trustors send about 50% of their endowment on average in the trust game, and

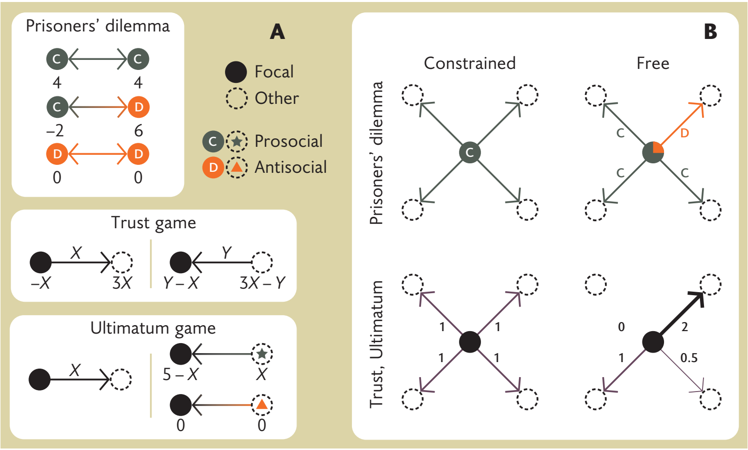

Fig. 1 Schematics of our experiment for the three economic games. (A) In the prisoner's dilemma, players choose between cooperation and defection, with payoffs dependent on their own actions and those of their neighbours. The trust and ultimatum games are two-stage games. In the trust game's first stage, the trustor decides the number of tokens to send to the trustee, who then receives triple the amount and determines how many to return to the trustor. The first stage of the ultimatum game involves the proposer deciding on the distribution of a given number of tokens. In the second stage, the responder opts to accept or reject the proposal. If accepted, both players receive the proposed amounts; if rejected, both receive nothing. (B) Differences between constrained and free players in the prisoner's dilemma, and the first stage of the trust and ultimatum games. Constrained players make decisions at the neighbourhood level, while free players make individualized decisions for each neighbour. For the prisoner's dilemma, this manifests as the freedom to choose actions for each neighbour separately, and in the trust and ultimatum games as the freedom to entrust or propose varied amounts to different neighbours.

trustees return slightly less. In the ultimatum game, proposers typically offer between 40% and 50% of the endowment, which responders accept while regularly rejecting smaller offers [18, 19]. In repeated games, players generally exhibit higher levels of prosocial behaviour compared to one-shot games, as repeated interactions allow for strategy development based on past experiences and expectations of future encounters [20, 21].

The discrepancy between theoretical predictions and experimental outcomes in games on networks unfolds in a slightly different manner. Here, theory suggests that homogeneous networks should promote prosocial behaviour relative to well-mixed populations and heterogeneous networks relative to homogeneous ones [22, 23]. However, numerous laboratory experiments have failed to find a significant difference between cooperation levels in well-mixed populations, homogeneous networks, and heterogeneous networks [24], except under very specific conditions [25].

To investigate whether the ability to act differently towards individual neighbours enhances prosocial behaviour, we designed games on a lattice network with two player types, constrained and free. Constrained players adhere to traditional games on networks setups, where the focal player performs a single action per round for the entire neighbourhood, regardless of the number of neighbours [7, 8, 22, 23, 26, 27]. In contrast, free players represent a less explored approach that grants greater agency. This agency is often modeled through dynamic networks where players can adjust their connections to exclude defectors, which typically results in higher cooperation levels than in static networks [28–30]. Alternatively, allowing players to interact individually with each neighbor has been theoretically shown to affect cooperation [31]. However, this effect is not necessarily positive, as some models indicate that cooperation is optimized in mixed populations [32], while others suggest that free players can also have a negative effect on cooperation in heterogeneous networks [33]. We tailored the latter approach for each game's specifics (Fig. 1).

In the prisoner's dilemma, constrained players were restricted to cooperating or defecting with all neighbours simultaneously, as in standard models of games on networks. Free players, conversely, could choose actions for individual neighbours (Fig. 1A).

The trust game comprised two stages. First, all players acted as trustors with neighbours, then as trustees. Constrained trustors could entrust the same token amount to all neighbours, while free trustors could vary their contributions (Fig. 1B). In the second stage, there was no differentiation between constrained and free trustees, and the returned amounts were distributed equally among neighbours.

Similarly, the ultimatum game proceeded in two stages. In the proposer stage, constrained proposers could offer an identical token amount to all neighbours, whereas free proposers had the flexibility to propose individualized amounts (Fig. 1B). In the responder stage, both constrained and free players had the option to accept or reject proposals from each neighbour independently.

We employed a control group and four treatment groups for each game. The control group was composed solely of constrained players, representing a conventional spatial game theory setup. In contrast, the four treatment groups saw a progressive reduction in these constraints by incrementally increasing the fraction of free players within the total population to low (e.g. 25%), medium (e.g. 50%), high (e.g. 75%), and finally, a full (e.g. 100%) free-player population. The primary purpose of adjusting the fraction of free agents was to validate the difference between constrained and free experimental designs. Having treatments with both constrained and free players also addresses asymmetric games, which were developed to capture individual differences among players. Such games are typically characterized by heterogeneous payoffs or varying networking capabilities [34–36]. Lastly, players were aware of the type of their neighbouring players. For comprehensive details, refer to the Methods section.

Cooperation, trust, and fairness

Allowing players to interact differently with their individual neighbours enhances prosociality, leading universally to increased cooperation, trust, and fairness (Fig. 2). This is evident in the prisoner's dilemma as a steady rise in the frequency of cooperation with an increasing fraction of free players in the population. Compared to the control group, cooperation increases progressively in mixed populations with varying densities of free players, peaking in the population of free players (Fig. 2A). The trust game results display a comparable pattern, with the lowest entrusted amount in the population of trustors. This is succeeded by a steady increase in mixed populations, culminating in a population composed entirely of free trustors (Fig. 2B). As the trust game is a two-stage game, we also noted a similar increasing pattern in the amount returned by trustees in the second stage (Extended Data Fig. 1A).

In the ultimatum game, the proposed amounts in the population of constrained proposers are lower than those in the population of free proposers (Fig. 2C). However, mixed populations exhibit less sensitivity to the increasing fraction of free players. The proposed amounts are slightly lower in treatments with a low and medium fraction of free players compared to the population of constrained proposers, but slightly higher in the population with a high fraction of free players. A similar pattern is observed for the accepted amounts in the second stage (Extended Data Fig. 1B).

We then examined how players use their social networking agency over time (Extended Data Fig. 2). In populations of free players, the first-round cooperation, entrusted amount, and proposed amount increase considerably relative to populations of constrained players. In mixed populations, these variables generally increase with a higher fraction of free players, but not consistently. Across the rounds, the trend is stable and often slightly negative, rarely significant (Extended Data Table 1 and 2).

These findings indicate that free players express their prosocial tendencies from the first round, rather than relying solely on learning and optimization through repeated interactions.

An examination of the impact of higher prosociality on wealth reveals that in all three economic games, wealth generally increases, more so among free players compared to their constrained counterparts (Extended Data Fig. 3A-C). Inequality is typically lower in populations of constrained and free players, with the latter having lower levels. However, in mixed populations, we observe higher inequality at lower fractions of free players,

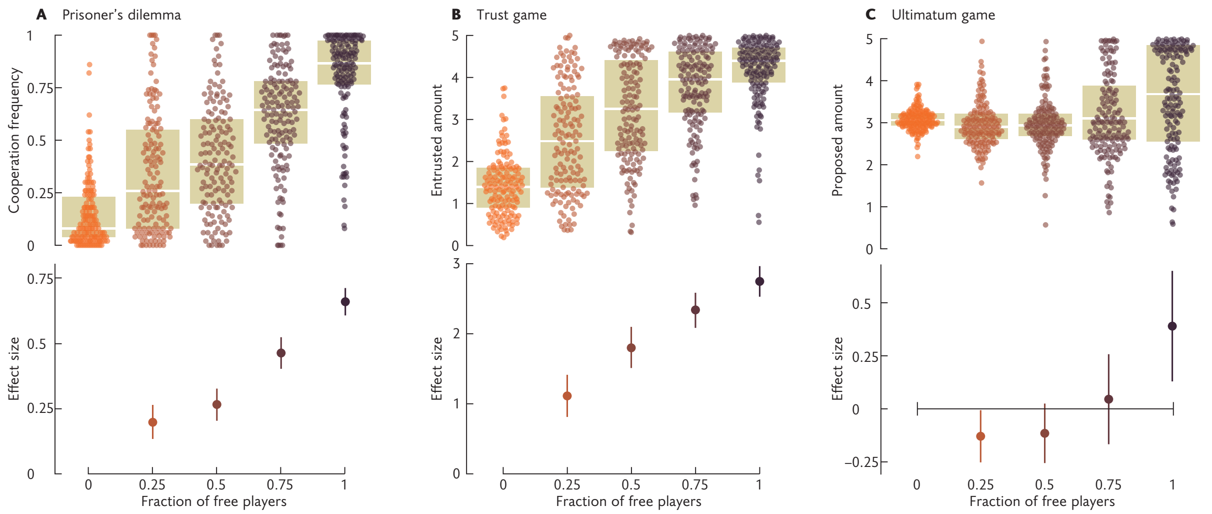

Fig. 2 Social networking agency universally enhances cooperation, trust, and fairness. Displayed are the results across the control group and four treatment groups in (A) the prisoner's dilemma, (B) the trust game, and (C) the ultimatum game. Each game comprized a control group with a population of constrained players and three treatments with mixed populations, including low, medium, and high fractions of free players, as well as a treatment with a population entirely composed of free players. An increase in the fraction of free players in the population leads to elevated levels of cooperation, trust, and fairness, as indicated by the frequency of cooperation, the entrusted amount, and the proposed amount, respectively. The second stage of the trust and ultimatum games exhibits a similar pattern (Extended Data Fig. 1). Statistical significance was evaluated using the Bonferroni correction.

which then decreases with an increased proportion of free players. This pattern is consistent in both the prisoner's dilemma and trust game (Extended Data Fig. 3D, E). In the ultimatum game, inequality rises with more free players but falls entirely in the free population (Extended Data Fig. 3F). A closer look at the different stages of the games reveals additional differences between the trust and ultimatum games. In the former, wealth increases for both trustors and trustees as the number of free players grows (Extended Data Fig. 3G), while in the latter, proposers' wealth initially rises and then falls, but responders' wealth consistently increases (Extended Data Fig. 3H). Inequality trends are also distinct. In the trust game, it increases for trustors with more free players and varies for trustees (Extended Data Fig. 3I), whereas, in the ultimatum game, it steadily rises for both proposers and responders (Extended Data Fig. 3J).

Finally, since players have information about whether their neighbours are constrained or free types, we analyzed the data for potential same-type biases in first-round interactions, prior to the influence of learning or experience. However, our analysis did not reveal any strong or consistent differences in behaviour across the games or between the different types of players (see Supplementary Information for a detailed overview).

These findings imply that the low inequality observed in control groups is a result of the restrictive environment, where players cannot optimize their strategies and, thus, often resort to antisocial behaviour. Mixed populations experience an increase in inequality as free players utilize their social networking agency. However, in entirely free populations, the playing field is level, leading to both the highest wealth and the lowest levels of inequality.

Behavioural phenotypes

Next, we derived behavioural phenotypes for each game using explanatory data mining (Fig. 3). Experimental studies often classify behaviour into a few stable clusters [37, 38], a pattern also evident in our data. In the prisoner's dilemma, players are categorized as prosocial, conditional, or antisocial based on their overall cooperation frequency and the probability of cooperating in response to the previous round's circumstances (Fig. 3A). A population of constrained players primarily consists of antisocial players who defect in most interactions. As the fraction of free players increases,

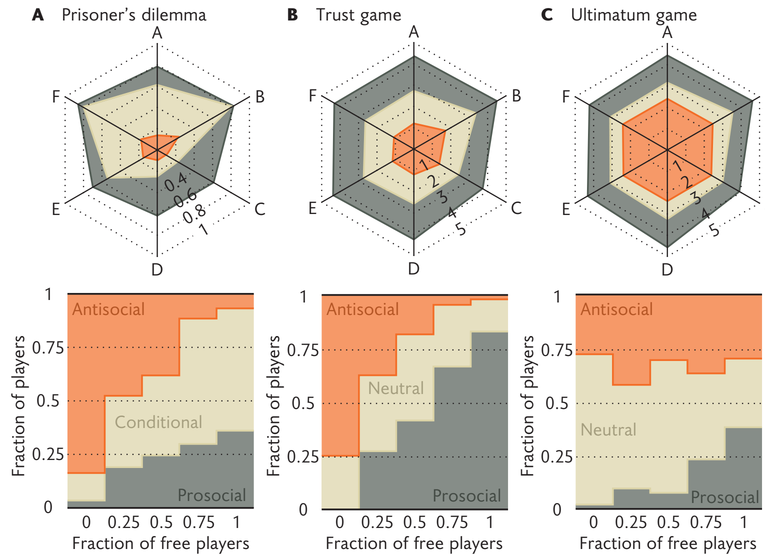

Fig. 3 Prosocial behaviour emerges more readily in increasingly free populations. The behavioural phenotypes displayed are derived from explanatory data mining based on six empirical behavioural variables. In all three economic games, Clustering Factor A represents the overall result (cooperation frequency, entrusted amount, and proposed amount, respectively), while clustering factors B-F depend on the circumstances of the previous round (for more details, see Methods). A) In the prisoner's dilemma, we identify prosocial, conditional, and antisocial behavioural phenotypes. The fraction of prosocial and conditional players increases with the fraction of free players. B) and C) In the trust and ultimatum games, a neutral phenotype emerges in place of the conditional phenotype. In the trust game, a higher fraction of free players results in prosocial trustors becoming the majority. In the ultimatum game, prosocial proposers are slightly more represented than the other two phenotypes, but only in the final treatment. For additional results see Extended Data Fig. 4 to 7.

there is a significant rise in the number of conditional cooperators, who typically employ the "tit-for-tat" strategy—defecting in response to defection and cooperating in response to cooperation—and prosocial players, who generally cooperate. In the free-player population, conditional cooperators are the majority, followed by prosocial players. This suggests that the high prevalence of antisocial players in the control group likely results from the constrained environment rather than inherent antisocial tendencies.

In the trust game, we identified behavioural phenotypes—prosocial, neutral, and antisocial—distinguished by the average overall trust they extend and the average amounts in response to the previous round's circumstances. Similar to the prisoner's dilemma, the constrained trustor population primarily consists of antisocial players. However, increasing the proportion of free players results in a gradual rise in the number of prosocial trustors, eventually making them the majority, while the numbers of neutral and antisocial trustors decrease (Fig. 3B). Extracting the behavioural types for trustees revealed an increasing prevalence of the neutral phenotype as the proportion of free players rises, with the number of prosocial trustees also increasing and antisocial trustees decreasing (Extended Data Fig. 4). We also tested whether players' behaviour is consistent across different stages of the game—for instance, whether a prosocial trustor is also a prosocial trustee. Our findings confirm this, as prosocial trustors return the highest amounts when acting as trustees, followed by neutral and then antisocial trustors (Extended Data Fig. 5).

The defined clustering factors could not detect conditional behaviour in the trust game, as free trustors may respond to lower trustee returns by redistributing their endowment among other neighbours, thus maintaining their average entrusted amounts. To confirm the existence of conditional behaviour, we examined how trustors react to trustee returns and found that trustors tend to increase their entrusted amounts in response to receiving larger returns from trustees (Extended Data Fig. 6).

Behavioural phenotypes in the ultimatum game, characterized by the average proposed amounts overall and in response to the previous round's circumstances, reflect those observed in the trust game (Fig. 3C). However, the distinction

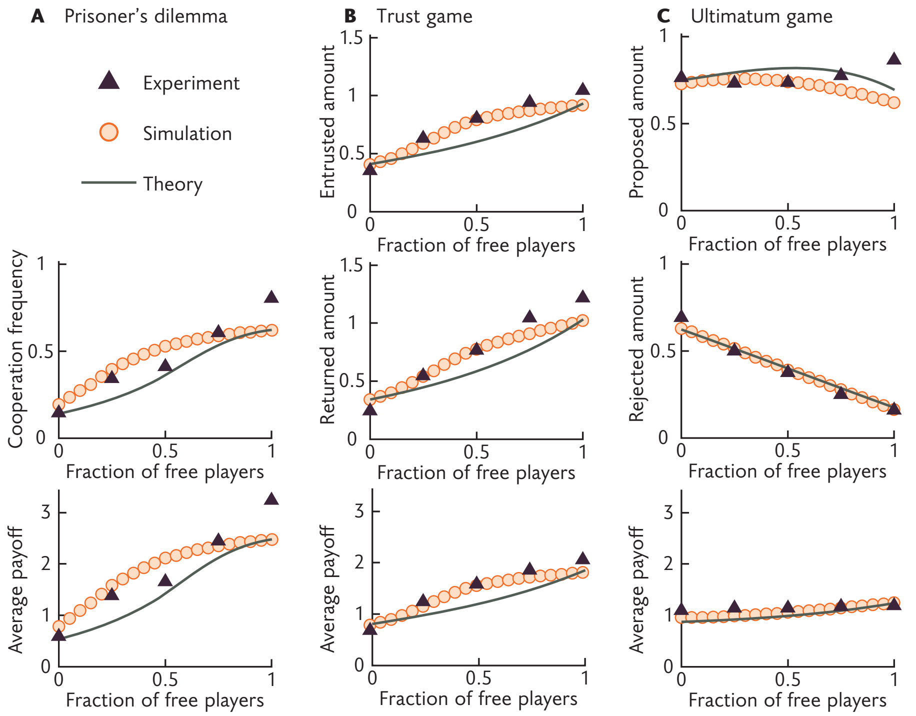

Fig. 4 Computational and theoretical analyses elucidate the observed experimental results. (A) For the prisoner's dilemma, we present experimental, computational, and theoretical results for both the frequency of cooperation and the average payoff. (B) For the trust game, we display experimental, computational, and theoretical results for the entrusted amount, the returned amount, and the average payoff. (C) For the ultimatum game, we present experimental, computational, and theoretical results for the proposed amount, rejected amount, and average payoff.

between antisocial and neutral players is less pronounced here than in the trust game. This can be attributed to the second-stage players in the ultimatum game controlling the rejection punishment mechanism, thereby maintaining minimal offers at relatively higher levels. This difference is also evident in the distribution of behavioural phenotypes across the control and treatment groups. In the constrained population, neutral proposers are predominant, followed by antisocial proposers. Conversely, prosocial proposers are most prevalent in the free population, although the difference from the other two phenotypes is not significant. The increase in prosocial proposers primarily occurs at the expense of neutral proposers, while the number of antisocial proposers remains relatively stable between constrained and free populations. The behavioural types of responders mirror those of proposers (Extended Data Fig. 4). Antisocial responders dominate in the constrained population, while prosocial responders are slightly more prevalent in the free population. Similar to the trust game, we found that proposers' behaviour remained consistent when they assumed the role of responders (Extended Data Fig. 5).

To assess conditional behaviour in the ultimatum game, we examined proposers' reactions to the acceptance and rejection of their previous round's proposals. We found a positive relationship with both outcomes (Extended Data Fig. 7). However, the narrow range of data points for proposals reacting to acceptance suggests that once proposers identify acceptable levels, they tend not to deviate significantly. Conversely, the wider range of data points in response to rejection indicates that proposers often increase their offers following a rejection, while some may offer less, possibly shifting their focus to other, presumably more agreeable, neighbours.

In summary, these results suggest that social networking agency promotes the proliferation of conditional behaviour in economic games. Furthermore, the similarity between the average entrusted and proposed amounts of antisocial and neutral players in these games to those observed in classical two-player experiments suggests that constrained players perceive their neighbourhood as a single entity, potentially affecting their understanding of fairness and trust. In contrast, free players regard each neighbour as an individual, facilitating a more prosocial distribution of their endowment.

Numerical analysis

To gain a deeper understanding of the mechanisms driving our results, we developed a model based on the simplest assumptions that align simulated behaviour with that of human participants: first-order conditional strategies, heterogeneity, and random mutation.

The general model, which is applicable to all three economic games, comprises an interaction structure and the evolution of strategies over time. Specifically, agents were positioned on a lattice network and randomly assigned as either constrained or free players. At each time step, they updated their strategies based on probabilities extrapolated from experimental data. The general model was further refined to accommodate the specifics of each game (see Methods and Supplementary Information for additional details).

In the prisoner's dilemma, computational and theoretical analyses centred on probabilities derived from players' behaviours in the first and previous rounds, successfully approximating the experimental results (Fig. 4A).

For the trust game, a more complex model was necessary. It required estimating both the amounts and probabilities for both stages of the game: the entrusted and returned amounts in the initial round, and the probabilities of trustors entrusting certain amounts based on their neighbours' behaviour in the previous round (Fig. 4B).

The ultimatum game necessitated the most intricate modelling. It involved estimating variables based on initial round proposal amounts and acceptance thresholds, as well as the probabilities of proposing certain amounts and acceptance thresholds, contingent upon neighbours' behaviours in the previous round (Fig. 4C).

In summary, our model demonstrates that player behaviour can be effectively replicated by primarily focusing on their reactions to their neighbours' behaviour in the previous round. In doing so, it provides an algorithmic blueprint for understanding human behaviour in the prisoner's dilemma, trust game, and ultimatum game, while revealing the distinct levels of complexity among these economic games.

Discussion

The study demonstrates that the freedom to interact differently with individual neighbours enhances cooperation, trust, and fairness, compared to the unrealistic constraint prevalent in the literature—that agents must behave identically towards their entire social neighbourhood. We observe higher payoffs and lower inequality than in the constrained reference experiments. These findings suggest that much of the literature on social dilemmas on social networks underestimates the prosociality of the actual situations their studies aim to model [23]. Reality is more cooperative than science has thus far suggested.

Our results from the constrained control group align with previous studies on the prisoner's dilemma, where initial cooperation starts at approximately 40% and then steadily declines [24]. In contrast, in the treatment with free players, first-round cooperation started at 73% and averaged around 81% throughout the game, reflecting high cooperation rates comparable to those observed in dynamic networks [28–30]. The trust and ultimatum games, however, provide new insights, as these games are rarely studied on networks experimentally. Interestingly, the average first-round outcomes are relatively consistent with those observed in one-shot two-player games [19]—constrained players entrusted 43% and proposed 58% of their endowment on average. In repeated trust and ultimatum games, players typically maintain similar offers to those observed in one-shot games [39–42]. In our study, constrained players entrusted an average of 28%, while proposed amounts slightly increased to 62%, indicating that constrained networks undermine initial cooperation and trust, whereas fairness remains relatively stable. However, free populations exhibited significant increases in prosocial behaviour; first-round and average entrusted amounts rose to 86% and 84%, respectively, with the proposed amount in the first round and overall staying around 70%.

In our mixed treatments, players experience asymmetric interactions. Typically, inequality on networks is explored by assigning different payoffs or endowments to players. While heterogeneous endowments generally reduce cooperation [43], research has shown that, on social networks, inequality must be visible to players to significantly decrease cooperation [44]. Conversely, in scenarios where players differ in productivity, a certain degree of endowment inequality may be essential for sustaining cooperation [45]. In our study, inequality in earned payoffs arises from free players having the ability to adjust their behaviour to individual neighbours. Although players were aware of their neighbours' types, their first-round interactions did not exhibit strong or consistent same-type bias.

By overcoming the constraints of traditional network-based experiments, this study paves the way for many interesting future directions. An evident next step towards increasing realism is to remove the anonymity of the experiments (which we maintained to isolate our topical mechanism) to enable human social sensing [46, 47]. Reduced anonymity would also facilitate studies of in-group favouritism—an additional sociopsychological effect reflected in the wiring of social networks [48, 49]. While our study focuses on how people use their social network, it would be interesting to enhance the realism concerning network structure [8] and the ability to modify one's social network connections [50], while being mindful of logistical and technological challenges of scaling up the experiments [51]. Evaluating the impact of social networking agency on collective actions in public and common good provision and maintenance also deserves attention [52]. Finally, our findings lay a foundation for further theoretical and experimental exploration of trust and ultimatum games on networks—topics almost absent in the current literature. This includes examining whether differences in how constrained and free players perceive their neighbourhoods depend on the number of decisions or interactions they have in each round.

If social networks—crucial in coordinating social life, including acts of prosociality—also instil a more prosocial mindset in people more directly, one might speculate that cooperation and social networking ability emerged concurrently. This aligns with the interdependence hypothesis of anthropology [53], which posits that when communities of prehistoric humans began facing competition from other communities, many of the defining characteristics of social organising appeared—fundamentally a "group-mindedness" characterized by a "collective intentionality" [53].

Methods

Experiment

Ethical approval declarations and preregistration. This study was approved by the Northwestern Polytechnical University Ethics Committee on the use of human participants in research, and carried out in accordance with all relevant guidelines. Informed consent was obtained from all participants. The trust and ultimatum games were preregistered (https://aspredicted.org/KFF_YQK). The prisoner's dilemma game was not included in the preregistration as some data had already been collected by the time the preregistration was submitted.

Structure and setup. The experimental design embedded three economic games – the prisoner's dilemma, the trust game, and the ultimatum game – into a network structure. Volunteers were placed on a 7×7 two-dimensional lattice and randomly assigned as *constrained* or *free* player types. In each round, constrained players could only perform identical actions towards all four neighbours, while free players could vary their actions.

Each game included a control group of solely constrained players. Additionally, four treatment groups were established, each with varying fractions of free players: 25%, 50%, 75%, and 100%. Over 50 rounds, players interacted with their four neighbours, with player types and neighbours remaining constant. Players were able to see the type of their neighbouring players.

In the prisoner's dilemma, constrained players had to uniformly decide to either cooperate or defect with all neighbours. Conversely, free players could tailor their strategies for each neighbour (Fig. 1).

The trust and ultimatum games unfolded in two stages. The first stage involved the classification into constrained and free players, with no differentiation in the second stage. This design aimed to assess whether the presence of free players would influence prosocial behaviour even in a scenario with minimal deviations from the control group setup.

In the trust game's first stage, all participants, acting as trustors, decided the amount of tokens to entrust to their neighbours. In the second stage, all players, now trustees, decided how many tokens to return (Fig. 1A). Constrained trustors could only entrust an identical token amount to all neighbours, while free trustors could vary the amounts to each neighbour (Fig. 1B). Both types of trustees could only select a single amount to be returned, which was then equally divided among all four neighbours.

In the ultimatum game's first stage, all participants, acting as proposers, decided on a token division for their neighbours. In the second stage, now responders, they chose to either accept or reject the proposed token distribution. If a proposal was rejected, both the proposer and the responder received no payoff (Fig.1A). Constrained proposers had to offer the same token amount to all neighbours, while free proposers could propose varied amounts (Fig. 1B). Both types of responders could individually accept or reject proposals.

Player recruitment. Across all three games, we conducted 15 sessions, each with 49 volunteers and three replications per treatment, resulting in a total of 45 sessions. We recruited 2205 undergraduate students from seven universities in the northern, northwestern, and southwestern regions of China. The participants were 54.3% female and 45.7% male, with an average age of 19.7 years. A more detailed demographic breakdown is available in the Supplementary Information.

Each volunteer participated in a single session. To minimize the impact of known interactions, we ensured that the participants were from different classes and remained anonymous throughout the experiment. Upon arrival at the computer lab, volunteers were randomly assigned to individual computer cubicles. The screens displayed the instructions for the experimental procedures (see Supplementary Information). The formal experiment began only after volunteers confirmed their understanding of the instructions through a questionnaire. Participants played 50 consecutive rounds of the game, accumulating tokens. To avoid end-of-treatment effects, the exact number of rounds was not disclosed to the participants.

Gameplay. In each round of the prisoner's dilemma game, volunteers had 30 seconds to make a decision using a personalized gameplay interface. The trust and ultimatum games, being two-stage games, required volunteers to play two roles in each round. In the trust game, volunteers initially acted as trustors, with 30 seconds to decide the number of tokens to entrust to their neighbours. Subsequently, they assumed the role of trustees, with another 30 seconds to determine the number of tokens to return. An additional 30 seconds was allocated for reviewing the results. In the ultimatum game, volunteers first acted as proposers, with 30 seconds to decide on a token division proposal for their neighbours. They then switched roles to responders, with another 30 seconds to accept or reject the proposal. The final 30 seconds were allocated for reviewing the results. Examples of interfaces for all three economic games can be found in the Supplementary Information.

Payoffs. We used the o-Tree platform to create the gameplay interface [54]. Each session lasted approximately 2 hours on average. In the prisoner's dilemma game, participants were endowed with an initial 50 tokens. Conversely, in the trust and ultimatum games, participants received a per-round allocation of five tokens. To incentivize participation, the total tokens accrued over all rounds were converted into real monetary rewards at a rate of RMB 1.0 per token. A show-up fee of RMB 20 was also awarded to each participant. Participants with a negative token balance were only eligible to receive the show-up fee. Upon completion of the experiments, participants were required to sign to verify their earnings.

In the prisoner's dilemma game, the average earnings amounted to RMB 443, with a range from RMB 20 to RMB 1024.

In the trust game, the average earnings stood at RMB 321, with a range from RMB 20 to RMB 676. For trustors, the calculation of payoffs included only the amounts returned by trustees, a measure implemented to prevent potential endowment hoarding throughout the repeated game.

In the ultimatum game, the average earnings were RMB 249, ranging from RMB 91 to RMB 350. Given that the proposer had to divide their endowment among four neighbours, each of whom could individually accept or reject the proposal, payoffs were computed by dividing the retained endowment by the number of neighbours who accepted the proposal and adding it to the payoffs from the accepted proposals.

Specific methods used for data analysis, statistical robustness, and figure generation. Fig. 2 presents the differences between the control group and the four treatments. The upper panels display the data distribution, median, and the 25th and 75th percentiles, while the lower panels include the effect size and confidence intervals. Statistical significance was calculated at the treatment level, but to ensure the robustness of our results against potential interdependencies between players, we also calculated standard errors clustered at the individual and session levels [55, 56]. The results are generally consistent with those at the treatment level. However, there are exceptions. For the first mixed treatment (25% of free players) in the trust game, statistical significance is lost at the session level. Similarly, in the ultimatum game, the third mixed treatment (75% of free players) loses statistical significance at both the individual and session levels. Notably, the results between purely constrained and purely free populations remain significant across all analyses (see Supplementary Information). The same applies to Extended Data Fig. 1.

Fig. 3 presents the results of clustering analysis on the experimental results in the prisoner's dilemma, and the first stage of the trust and ultimatum games. We applied the K-means clustering algorithm to identify behavioural phenotypes and used the Dindex and SDindex methods to determine the optimal number of clusters [57]. Data mining was based on six empirical behavioural variables (denoted as A - F in Fig. 3). In all three economic games, clustering factor A represents the average overall result, while clustering factors B - F are conditional on circumstances in the previous round.

In prisoner's dilemma, B to F represent cooperation probabilities and depend on the cooperative behaviour of focal player and their neighbours in the previous round:

A - cooperation frequency;
B - probability of playing C after focal player played C in the previous round;
C - probability of playing C after focal player played D in the previous round;
D - Probability of playing C after up to one neighbour played C;
E - probability of playing C after exactly two neighbours played C;
F - probability of playing C after at least three neighbours played C.

In the trust game, B to F represent the average amounts sent by the trustor and depend on the behaviours of the trustors and trustees in the previous round:

A - entrusted amount;
B - entrusted amount after the trustor sent four or more in the previous round;
C - entrusted amount after the trustor sent less than four in the previous round;
D - entrusted amount when up to one neighbouring trustee returned an amount equal to or greater than the trustor's previous send;
E - entrusted amount when exactly two neighbouring trustees returned an amount equal to or greater than the trustor's previous send;
F - entrusted amount when at least three neighbouring trustees returned an amount equal to or greater than the trustor's previous send.

In the ultimatum game, B to F represent the average amounts proposed by the proposer and depend on the amounts proposed by proposers and those accepted by responders in the previous round:

A - proposed amount;
B - proposed amount after the proposer sent four or more in the previous round;
C - proposed amount after the proposer sent less than four in the previous round;
D - proposed amount when up to two neighbouring responders accept the proposal in the previous round;
E - proposed amount when exactly three neighbouring responders accept the proposal in the previous round;
F - proposed amount when exactly four neighbouring responders accept the proposal in the previous round.

The same clustering methods have been applied to Extended Data Fig. 4 and 5. For a detailed overview, please see the Supplementary Information.

Model

Structure and setup. By adhering to a set of simple assumptions—first-order conditional strategies, heterogeneity, and randomness—we replicate the experiment using computational and mathematical models. This approach aims to facilitate a more comprehensive understanding of the mechanisms that underpin the outcomes observed in our experiment.

All three economic games have the same structure: they are set on a homogeneous network with periodic boundaries, comprising G nodes with a degree of k. Each node on the network is occupied by an individual agent, resulting in a total of G agents who are labelled as $\mathcal{G} = \{1, \cdots, G\}$. The connections between nodes are represented by $\{w_{ij}\}_{i,j\in\mathcal{G}}$, where $w_{ij} = 1$ (resp. $w_{ij} = 0$) signifies a connection (resp. no connection) between nodes i and j. A fraction F of players are randomly designated as free, while the remaining players are classified as constrained. We denote the player type in node i as v_i, where $v_i = 1$ (resp. $v_i = 0$) indicates a free agent (resp. constrained agent).

Prisoner's dilemma. The prisoner's dilemma is a single-stage game, structured as previously described. Agents decide whether to cooperate or defect and receive payoffs based on a payoff matrix.

Let s_{ij} denote player i's action towards j, where $s_{ij} = 1$ means cooperation and $s_{ij} = 0$ defection. For each free agent, the strategy is described by $(p^f;\ p^f_C, p^f_D)$, and, for each constrained agent, the strategy is $(p^c;\ p^c_{Ck_C}, p^c_{Dk_C})$. The notations are explained below. The system updates are as follows:

In time step $t = 0$, player i with $v_i = 1$, towards a neighbour j, chooses cooperation with probability p^f (i.e. $s_{ij} = 1$) and defection (i.e. $s_{ij} = 0$) otherwise. Player i with $v_i = 0$, cooperates with probability p^c—that is, $s_{ij} = 1$ for all $j \in \mathcal{N}_i$ (the set of i's neighbours)—and defects otherwise.

At each time step, all players update their actions across all interactions. We begin with the action update of a free agent i towards j.

(i) For $s_{ji} = 1$, agent i takes action $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability p^f_C (resp. $1 - p^f_C$) in the next round;
(ii) For $s_{ji} = 0$, agent i takes action $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability p^f_D (resp. $1 - p^f_D$) in the next round;

Next, we consider the action updating of a constrained agent i towards all $j \in \mathcal{N}_i$ (the set of i's neighbours).

(i) For $s_{ij} = 1$, if agent i has k_C cooperative neighbours, agent i takes action $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability $p^c_{Ck_C}$ (resp. $1 - p^c_{Ck_C}$) in the next round;
(ii) For $s_{ij} = 0$, if agent i has k_C cooperative neighbours, agent i takes action $s_{ij} = 1$ (resp. $s_{ij} = 0$)with probability $p^c_{Dk_C}$ (resp. $1 - p^c_{Dk_C}$) in the next round;

Supplementary Information C.1 contains the numerical simulation and theoretical analysis.

Trust game. The trust game unfolds in two stages, involving agents positioned within a predefined structure. In the first stage, agents, acting as trustors, allocate a certain number of tokens to their neighbours. This allocation is then tripled. In the second stage, agents, now acting as trustees, decide how many of the received tokens to return to their neighbours.

For simplicity, we divide the entrusted amount into several intervals and study the agents' entrusted amount in different intervals, denoted by $\mathcal{S} = \{S_1, S_2, \cdots, S_s\}$. Let $A_{ij}(t)$ denote agent i's entrusted amount to neighbour j at time t and $R_i(t)$ denote agent i's returned amount to each neighbour. Note that constrained agent i's entrusted amounts are identical for all neighbours, whereas the free agent's entrusted amounts vary for each neighbour. We make the following two assumptions:

(i) The entrusted amount of constrained agent i to j at time step t, (i.e. $A_{ij}(t)$) depends on the entrusted amount to him by his neighbours in the previous time step (i.e. $(1/k)\sum_{\ell\in\mathcal{G}} w_{\ell i}A_{\ell i}(t-1)$), while the entrusted amount of a free agent i to j at time step t (i.e. A_{ij}) depends on the entrusted amount to him by his neighbour j in the previous time step (i.e. $A_{ji}(t-1)$);
(ii) The returned amount of an agent i (i.e. $R_i(t)$) depends on the entrusted amount to i in the current round (i.e. $(1/k)\sum_{\ell\in\mathcal{G}} w_{\ell i}A_{\ell i}(t)$). Let λ_c (resp. λ_f) denote the ratio of the returned amount to the entrusted amount of a constrained agent (resp. a free agent). That is, $R_i(t) = (3\lambda_c/k)\sum_{\ell\in\mathcal{G}} w_{\ell i}A_{\ell i}(t)$ for a constrained agent and $R_i(t) = (3\lambda_f/k)\sum_{\ell\in\mathcal{G}} w_{\ell i}A_{\ell i}(t)$ for a free agent.

Each agent's strategy refers to his current entrusted amount in response to the neighbours' entrusted amount in the previous round, and his current returned amount in response to the neighbours' entrusted amount in the current round. We use (x, y) to describe an entrusted amount in response to neighbours, where x represents the entrusted amount from neighbours in the previous round, and y represents the agent's entrusted amount in the current round. All possible entrusted amounts in response to neighbours are $\{(x, y)\}_{x,y\in\{1,2,\cdots,s\}}$. Let $p^c_{x,y}$ (resp. $p^f_{x,y}$) denote the probability of a constrained agent (resp. free agent) taking entrusted amount S_y in response to neighbours' entrusted amount S_x. Moreover, let p^c_x and p^f_x denote the entrusted amount at the first round.

Supplementary Information C.2 contains the numerical simulation and theoretical analysis.

Ultimatum game. The ultimatum game is played in two stages within the previously described structure. In the first stage, agents act as proposers and propose how to split an amount of tokens between themselves and neighbours. In the second stage, agents act as responders and decide whether to accept or reject the proposal. If they accept the proposal, proposers and responders receive payoffs as proposed, otherwise they receive nothing.

For simplicity, we divide the proposed amount into several intervals and study the agents' proposed amount in different intervals, denoted by $\mathcal{S} = \{S_1, S_2, \cdots, S_s\}$. In the responder stage, the set of optional responses is also $\mathcal{S}$.

Let $P_{ij}(t)$ denote agent i's proposed amount to j at time step t, and $R_i(t)$, the threshold for agent i to accept the proposal. Note that constrained agents make the same proposal for all neighbours, while free agents make different proposals against different neighbours. Every constrained agent is assumed to have an identical threshold of acceptance for all neighbours, while a free agent has four possibly different thresholds of acceptance against four neighbours. We make the following assumptions:

(i) Proposed amount and acceptance threshold of constrained agent i to j at time step t (i.e. $P_{ij}(t)$ and $R_i(t)$) depends on their proposed amount in the previous time step and the perceived acceptance threshold of neighbours (i.e. $P_{ij}(t-1)$ and $\tilde{R}^c_i(t-1)$), including neighbours' proposed amount and i's acceptance threshold (i.e. $(1/k)\sum_{\ell\in\mathcal{G}} w_{\ell i}P_{\ell i}(t-1)$ and $R_i(t-1)$). The perceived acceptance threshold of constrained agent i towards their neighbours is

$$\begin{aligned}&\tilde{R}^c_i(t-1)\\ =&P_{ij}(t-1)\\ &+\left(1-\frac{1}{k}\sum_{\ell\in\mathcal{G}} w_{\ell i}\Theta(P_{i\ell}(t-1)-R_\ell(t-1))\right)\Delta,\end{aligned} \tag{1}$$

where $\Theta(x)$ is Heaviside Function with $\Theta(x) = 1$ for $x > 0$ and $\Theta(x) = 0$ otherwise, and Δ is the increment to adjust one's perception to the neighbours' acceptance threshold. An increasing number of i's neighbours accepting i's proposed amount means that i's current proposed amount is more likely to be higher than neighbours' acceptance threshold;

(ii) Proposed amount and acceptance threshold of free agent i to j depends on their proposed amount in the previous time step to j and the perceived acceptance threshold of neighbour j (i.e. $P_{ij}(t-1)$ and $\tilde{R}^f_i(t-1)$), including neighbour j's proposed amount and i's acceptance threshold (i.e. $P_{ji}(t-1)$ and $R_i(t-1)$). The perceived acceptance threshold of a free agent i towards their neighbours is

$$\begin{aligned}&\tilde{R}^f_i(t-1)\\ =&P_{ij}(t-1)+(1-\Theta(P_{ij}(t-1)-R_j(t-1)))\,\Delta.\end{aligned} \tag{2}$$

Each agent's strategy refers to his current proposed amount and acceptance threshold in response to his proposed amount and perceived neighbours' acceptance threshold, neighbours' proposed amount, and his acceptance threshold in the previous round. We use $(x_1, x_2, y_1, y_2;\ z_1, z_2)$ to describe proposed amount and acceptance threshold response, where $x_1, x_2, y_1, y_2, z_1, z_2$ respectively represents the agent's proposed amount and acceptance threshold in the previous round, the neighbours' proposed amount and perceived acceptance threshold in the previous round, and the agent's proposed amount and acceptance threshold in the current round. The set of all possible responses is $\{(x_1, x_2, y_1, y_2;\quad z_1, z_2)\}_{x_1,x_2,y_1,y_2,z_1,z_2\in\{1,2,\cdots,s\}}$. Let $p^c_{x_1,x_2,y_1,y_2;\, z_1,z_2}$ (resp. $p^f_{x_1,x_2,y_1,y_2;\, z_1,z_2}$) denote the probability to take proposed amount S_{z_1} and acceptance threshold S_{z_2} for a constrained agent (resp. a free agent) in the current round in response to his proposed amount S_{x_1} and acceptance threshold S_{x_2}, neighbours' proposed amount S_{y_1}, and perceived acceptance threshold S_{y_2} in the previous round. Let $p^c_{x_1,x_2}$ (resp. $p^f_{x_1,x_2}$) denote the probability that a constrained agent (resp. a free agent) uses proposed amount S_{x_1} and acceptance threshold S_{x_2} in the first round.

Let $\Omega_i(t)$ ($\bar{\Omega}_i(t)$) denote the set of agents whose proposed amount is accepted (rejected) by i, given by

$$\begin{aligned}\Omega_i(t) &= \left\{\ell \middle| w_{\ell i}\Theta(P_{\ell i}(t) - R_i(t)) \geq 0\right\},\\ \bar{\Omega}_i(t) &= \left\{\ell \middle| w_{\ell i}\Theta(P_{\ell i}(t) - R_i(t)) < 0\right\}.\end{aligned} \tag{3}$$

In the statistical analysis of experimental data, a constrained agent i's acceptance threshold is assumed to be

$$\hat{R}^c_i(t-1) = \begin{cases}\dfrac{\min\limits_{\ell\in\Omega_i(t-1)} P_{\ell i} + \max\limits_{\ell\in\bar{\Omega}_i(t-1)} P_{\ell i}}{2} & |\Omega_i(t-1)| > 0,\ |\bar{\Omega}_i(t-1)| > 0;\\ \max\limits_{\ell\in\bar{\Omega}_i(t-1)} P_{\ell i} + \Delta & |\Omega_i(t-1)| = 0;\\ \min\limits_{\ell\in\Omega_i(t-1)} P_{\ell i} - \Delta & |\bar{\Omega}_i(t-1)| = 0.\end{cases} \tag{4}$$

In the interaction with ℓ, $\overline{R^f_i}$ is the averaged value rejected by a free agent i, and the free agent i's acceptance threshold is assumed to be

$$\hat{R}^f_i(t-1) = \begin{cases}P_{\ell i} + \Delta & |\Omega_i(t-1)| = 0;\\ \overline{R^f_i} + \Delta & |\bar{\Omega}_i(t-1)| = 0.\end{cases} \tag{5}$$

For the given proposed amount setting $\mathcal{S} = \{S_1, S_2, \cdots, S_s\}$, the free agent's strategy $\left(p^f_{x_1,x_2}, p^f_{x_1,x_2,y_1,y_2;\, z_1,z_2}\right)$ and the constrained agent's strategy $\left(p^c_{x_1,x_2}, p^c_{x_1,x_2,y_1,y_2;\, z_1,z_2}\right)$ can be inferred from the experimental data.

Supplementary Information C.3 contain the numerical simulation and theoretical analysis.

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Data availability. The Open Science Framework page for this project (https://osf.io/n84dv/) includes all data from laboratory experiments.

Code availability. The codes for numerical analysis are available on the Open Science Framework (https://osf.io/n84dv/).

Author contributions. D. J., I.R., and Z.W. conceived the project. D.J. and I.R. designed the laboratory experiments. D.J. and Z.W. organized the experiments and collected data, supported by L.S., C.L., J. L., and X.L. D.J. and I.R. analysed data with inputs from and Z.W. and P.H. D.J., I.R., and P.H. prepared the figures. Q.S. and D.J. developed the numerical model. I.R. wrote the manuscript with inputs from D.J. and Z.W., and revisions from P.H.

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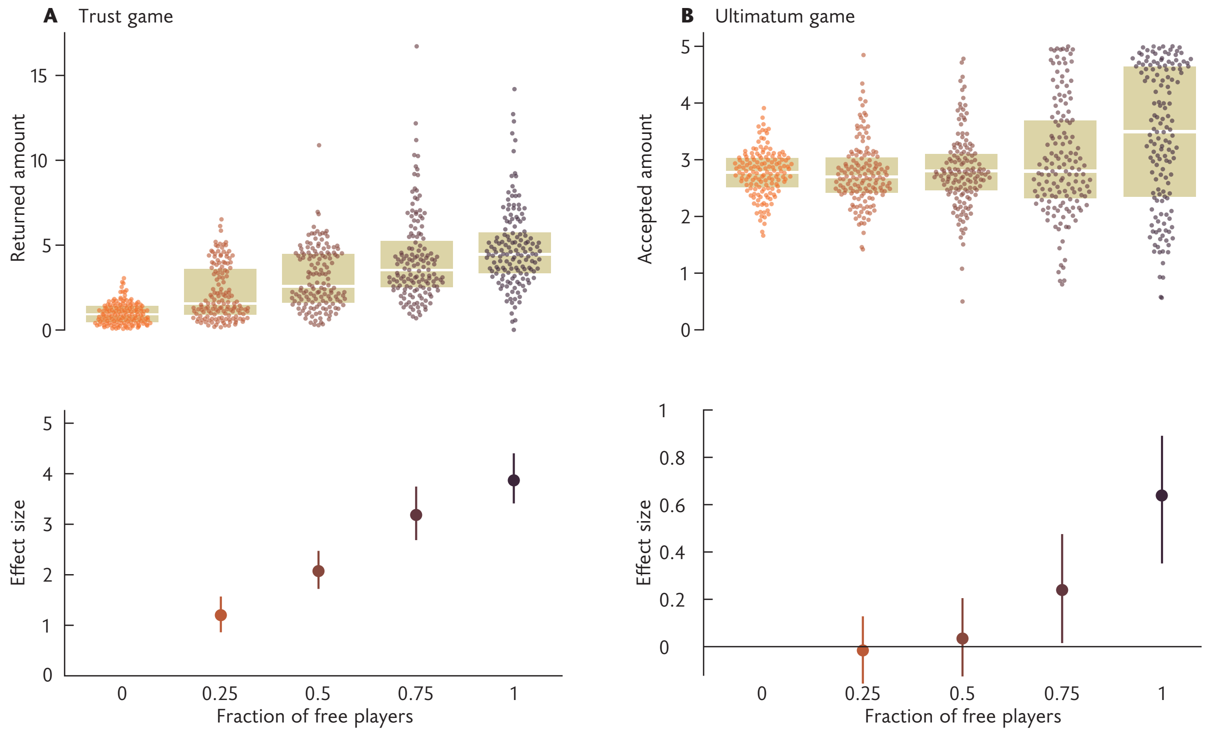
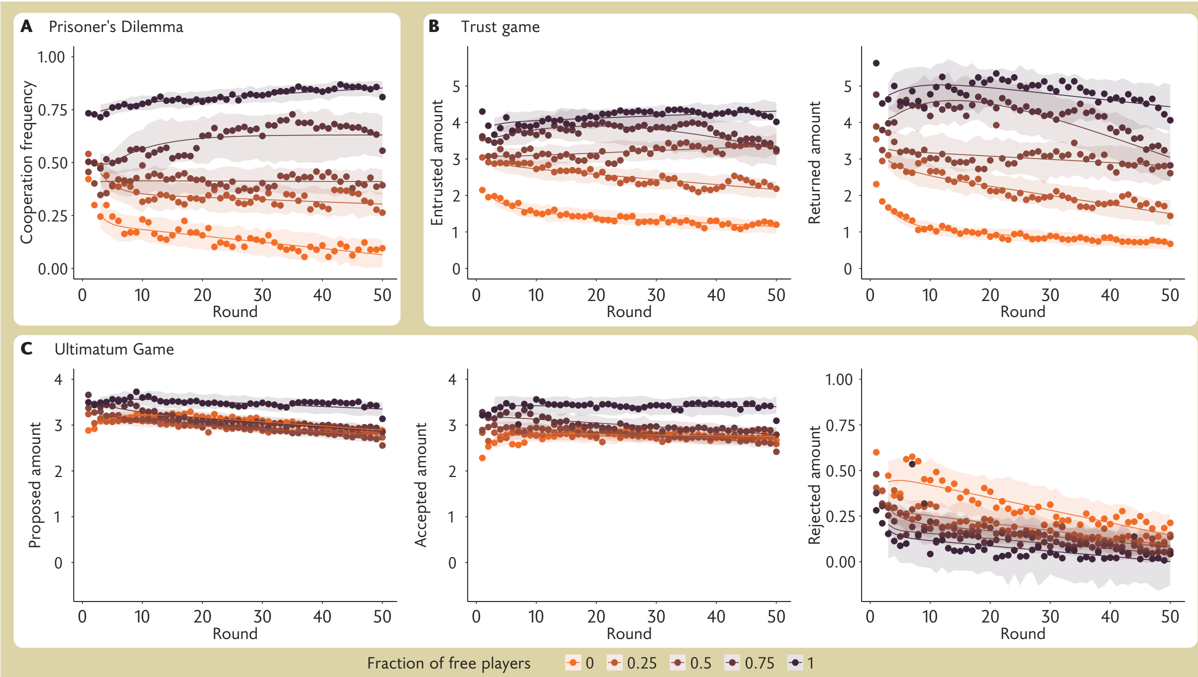
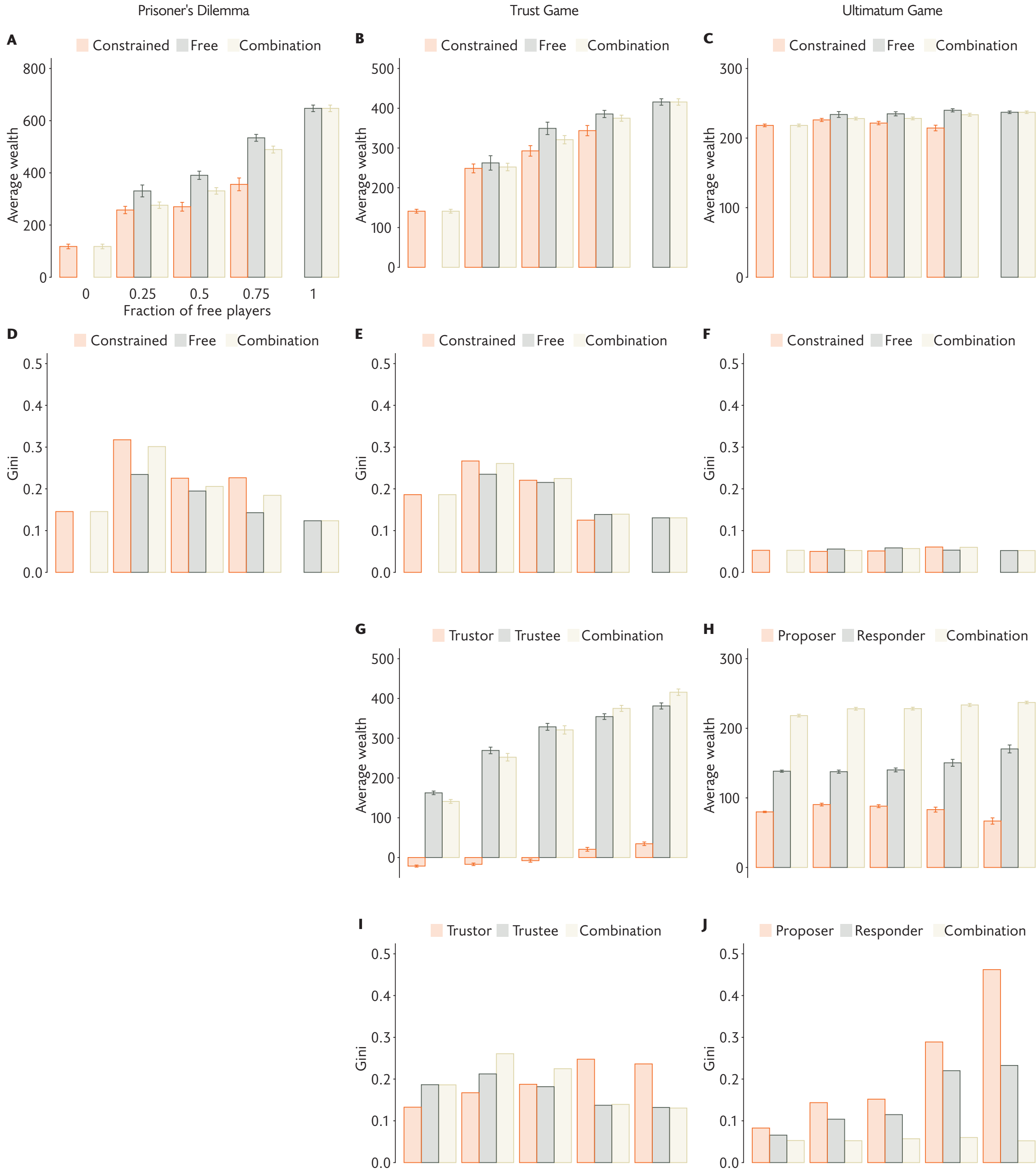


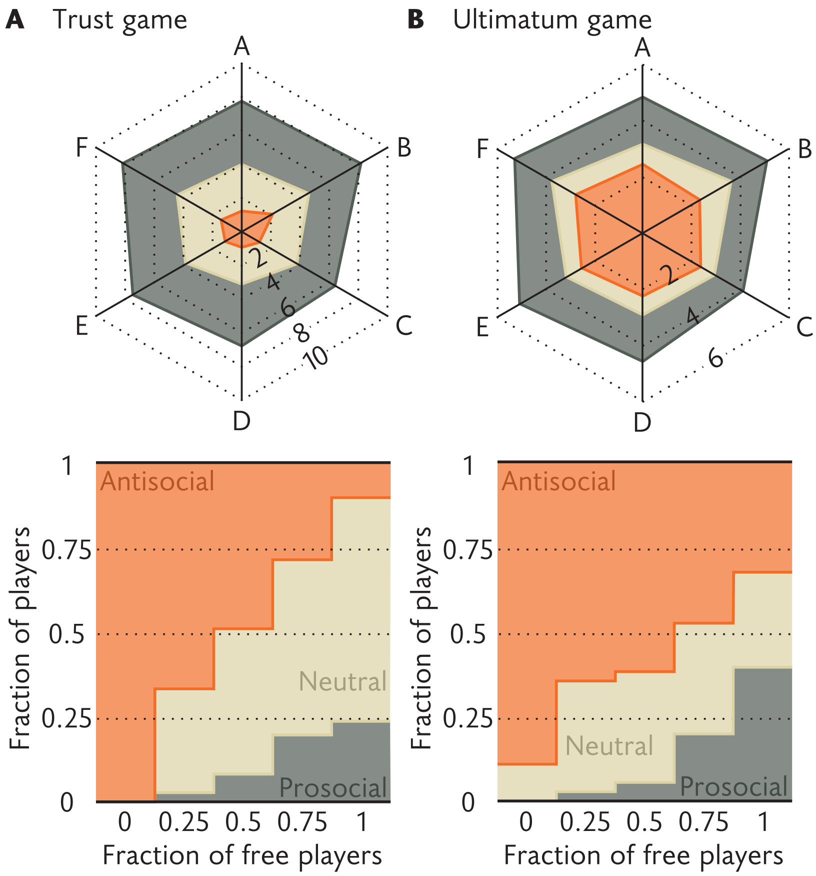
Extended Data Fig. 1 The second stage of the trust and ultimatum games follows a similar pattern as the first stage. Despite the absence of distinction between constrained and free players in the second stage, an increase in the fraction of free players typically results in a rise in (A) the returned amount in the trust game and (B) the accepted amount in the ultimatum game. Statistical significance was assessed using the Bonferroni correction.



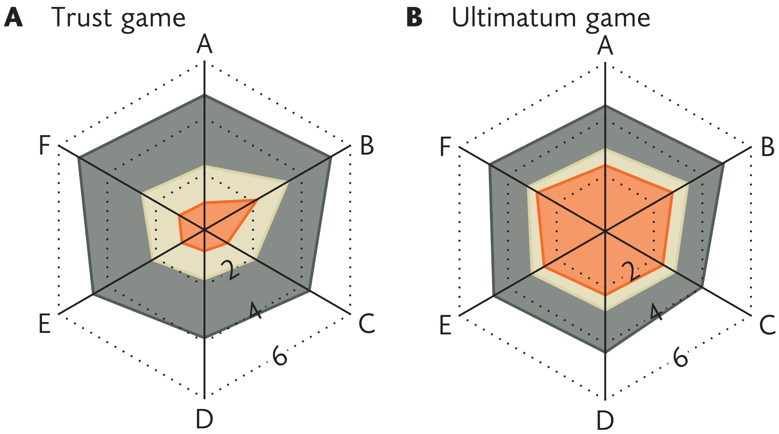
Extended Data Fig. 2 Cooperation, trust, and fairness surge when players are free to act differently with neighbours, often within the first round of the game. The figure depicts the temporal evolution of six variables across three games, each dataset representing the average of three replicates. The average and the 95% confidence bands of a time series model fitted to the data are also displayed (Extended Table 1 and 2). (A) In the prisoner's dilemma, the cooperation frequency shows a downtrend in the control group, a slight downtrend in mixed population treatments, and a slight uptrend in the free-player population treatment. (B) In the trust game, the entrusted amount exhibits a slight downtrend in the control and treatments with low and high densities of free players but a slight uptrend in the treatment with a medium density of free players and in the free-player population treatment. The returned amount shows a slight downtrend across both the control and all treatments. (C) In the ultimatum game, the proposed, accepted, and rejected amounts show a downtrend in control and across all treatments.



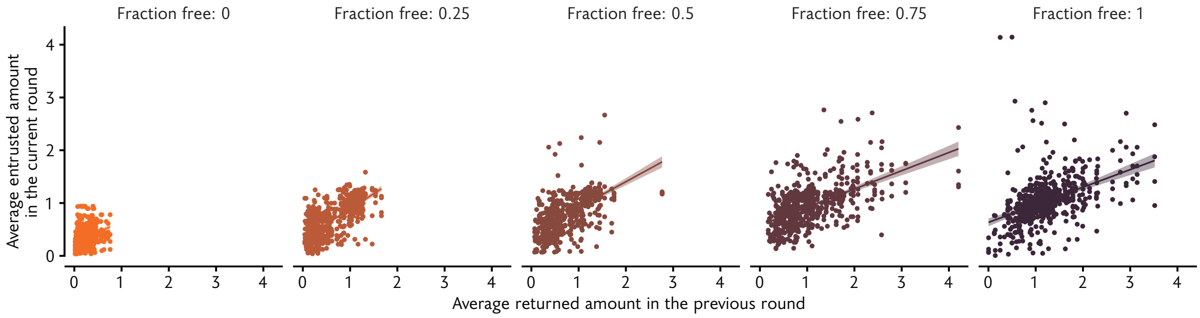
Extended Data Fig. 3 Social networking agency increases wealth and decreases inequality. The average wealth and the Gini coefficient are displayed, categorized by player type and game stage. (A-C) In the prisoner's dilemma and trust game, wealth based on player type increases steadily as treatments permit more free players. In the ultimatum game, wealth differences are subtle. However, free players are wealthier across all mixed treatment groups, reflecting their ability to optimize strategies for each neighbour. (D-F) In the prisoner's dilemma and trust game, inequality based on player type initially spikes in the second treatment, where free players are in the minority, and then gradually decreases to levels lower than in the initial treatment. In the ultimatum game, the situation is reversed. Inequality increases with the rising fraction of free players but drops when the population is entirely free, though with smaller variations in overall inequality levels. (J-K) Wealth disparities are more pronounced between stages of the game, as players in both games accrue most of their wealth in the second stage. While in the trust game, wealth consistently increases in both stages as the fraction of free players rises, in the ultimatum game, wealth in the proposer stage slightly decreases with a higher fraction of free players. (L-J) In the trust game, inequality based on game stage increases with a higher fraction of free players, reflecting the fact that more players in the population can optimize their strategies, leading to varying levels of success. In the ultimatum game, inequality increases in both stages, although overall inequality levels remain relatively similar.



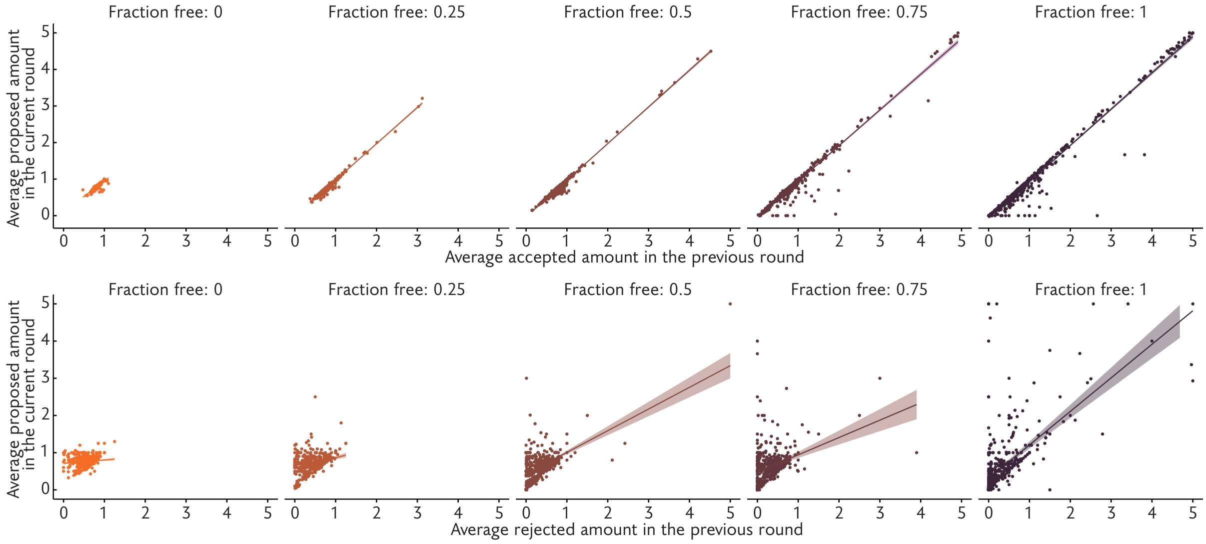
Extended Data Fig. 4 Behavioural phenotypes in the second stage of the trust and ultimatum games mirror those in the first stage. Using the six clustering factors from Fig. 3, we identify prosocial, neutral, and antisocial types in both stages of the games. A) In the second stage of the trust game, unlike the first stage where prosocial players predominate as the fraction of free players increases, neutral players become more prominent. The clustering factors represent average values in the current round for (A) the returned amount; (B) the returned amount after the trustee received four or more in the previous round; (C) the returned amount after the trustee received less than four in the previous round; and (D - F) the returned amount after up to one, exactly two, or at least three neighbouring trustors sent an amount equal to or greater than in the previous round; B) In the second stage of the ultimatum game, patterns resemble the first stage, with a relatively constant number of neutral players, but an increasing number of prosocial players and a decreasing number of antisocial players. The clustering factors represent average values in the current round for (A) the accepted amount; (B) the accepted amount after receiving a total offer of four or more in the previous round; (C) the accepted amount after receiving a total offer of less than four in the previous round; and (D - F) the accepted amount when up to two, exactly three, or exactly four neighbouring proposers propose an amount equal to or greater than in the previous round.



Extended Data Fig. 5 Player behaviour remains consistent across different stages of the trust and ultimatum games. Applying the same clustering factors as in Extended Data Fig. 3 to the behavioural phenotypes derived from the first stage of games reveals a consistent pattern of behaviour in the second stage. Specifically, if a player adopts a prosocial, neutral, or antisocial role in the first stage of the trust and ultimatum game, they are likely to maintain the same behaviour in the second stage.



Extended Data Fig. 6 Trustors tend to increase the amounts they entrust in response to larger returns received in the previous round. The presence of free players allows for more diverse strategies, observable in the spread of data points. This diversity is evident as some players opt to entrust less despite receiving more from neighbouring trustees in prior rounds. The regression slopes and their 95% CI are 0.39 with $[0.30, 0.48]$, 0.58 with $[0.53, 0.63]$, 0.49 with $[0.44, 0.54]$, 0.35 with $[0.30, 0.39]$, and 0.33 with $[0.28, 0.39]$, respectively. The regression intercepts and their 95% CI are 0.25 with $[0.23, 0.28]$, 0.31 with $[0.28, 0.34]$, 0.43 with $[0.38, 0.47]$, 0.58 with $[0.52, 0.63]$, and 0.63 with $[0.56, 0.71]$, respectively. The adjusted R^2 are $0.11(F = 72.98, P < 10^{-15})$, $0.48(F = 551.7, P < 10^{-15})$, $0.37(F = 342.2, P < 10^{-15})$, $0.30(F = 255.5, P < 10^{-15})$, and $0.19(F = 140.1, P < 10^{-15})$, respectively.



Extended Data Fig. 7 Proposers tend to increase their offers in response to acceptance and rejection in the previous round. This pattern is apparent from the narrow data range in the low fraction of free players' treatment, suggesting proposers adhere to successful offer amounts. In treatments with a majority of free players, some proposers opt to offer less despite previous acceptance, indicating a willingness to test established relationships and adjust responder expectations. However, when offers are rejected, proposers tend to increase their subsequent offers, suggesting they learn from rejection and attempt to make offers more appealing. The steeper slope with higher densities of free players might suggest that in a freer population, proposers encounter a variety of responder thresholds for acceptance, prompting them to adjust their offers upward to find a successful compromise. In the case of acceptance, the regression slopes and their 95% CI are 0.85 with $[0.81, 0.88]$, 0.99 with $[0.98, 1.01]$, 1.00 with $[0.99, 1.01]$, 0.98 with $[0.96, 0.99]$, and 0.99 with $[0.98, 1.01]$, respectively. The regression intercepts and their 95% CI are 0.10 with $[0.07, 0.13]$, -0.02 with $[-0.03, -0.01]$, -0.03 with $[-0.04, -0.02]$, -0.04 with $[-0.06, -0.02]$, and -0.06 with $[-0.09, -0.04]$, respectively. The adjusted R^2 are 0.80 ($F = 2320$, $P < 10^{-15}$), 0.97 ($F = 2.11 \times 10^4$, $P < 10^{-15}$), 0.98 ($F = 2.74 \times 10^4$, $P < 10^{-15}$), 0.95 ($F = 1.14 \times 10^4$, $P < 10^{-15}$), and 0.96 ($F = 1.45 \times 10^4$, $P < 10^{-15}$), respectively. In the case of rejection, the regression slopes and their 95% CI are 0.09 with $[0.03, 0.15]$, 0.27 with $[0.19, 0.35]$, 0.58 with $[0.51, 0.66]$, 0.47 with $[0.36, 0.58]$, and 0.90 with $[0.80, 1.00]$, respectively. The regression intercepts and their 95% CI are 0.71 with $[0.68, 0.75]$, 0.59 with $[0.55, 0.63]$, 0.42 with $[0.38, 0.47]$, 0.47 with $[0.42, 0.53]$, and 0.30 with $[0.24, 0.37]$, respectively. The adjusted R^2 are 0.02 ($F = 10.16$, $P < 0.01$), 0.09 ($F = 46.86$, $P < 10^{-10}$), 0.33 ($F = 239$, $P < 10^{-15}$), 0.13 ($F = 69.18$, $P < 10^{-15}$), and 0.39 ($F = 311$, $P < 10^{-15}$), respectively.

			Prisoner's dilemma			**Trust game**					
			Cooperation			**Entrusted**			**Returned**		
Summary (*model*)	Coefficients		Estimate	t-statistic	p-value	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
0% free	Constant	α_1	0.123	3.631	$< \mathbf{10^{-3}}$	0.435	2.411	0.020	0.315	3.561	$< \mathbf{10^{-3}}$
	Trend	α_2	−0.002	−2.938	**0.005**	−0.002	−1.499	0.141	−0.003	−2.233	0.031
	Stationarity	α_3	−0.583	−4.271	$< \mathbf{10^{-3}}$	−0.281	−2.773	**0.008**	−0.289	−4.336	$< \mathbf{10^{-4}}$
	Auto-correlative	α_4	−0.064	−0.545	0.589	−0.283	−2.193	0.034	−0.099	−0.930	0.357
			$R^2_{\text{adj}} = 0.297$			$R^2_{\text{adj}} = 0.244$			$R^2_{\text{adj}} = 0.325$		
25% free	Constant	α_1	0.125	3.297	**0.002**	0.678	2.126	0.039	0.735	2.293	0.027
	Trend	α_2	−0.0004	−1.206	0.234	−0.003	−1.781	0.082	−0.007	−2.070	0.044
	Stationarity	α_3	−0.352	−3.691	$< \mathbf{10^{-3}}$	−0.242	−2.217	0.032	−0.276	−2.505	0.016
	Auto-correlative	α_4	−0.025	−0.187	0.852	−0.098	−0.661	0.512	−0.185	−1.501	0.140
			$R^2_{\text{adj}} = 0.202$			$R^2_{\text{adj}} = 0.085$			$R^2_{\text{adj}} = 0.150$		
50% free	Constant	α_1	0.150	2.695	**0.010**	1.328	3.131	**0.003**	2.080	3.657	$< \mathbf{10^{-3}}$
	Trend	α_2	−0.00004	−0.147	0.884	0.003	1.949	0.058	−0.006	−2.096	0.042
	Stationarity	α_3	−0.363	−2.693	**0.010**	−0.437	−3.130	**0.003**	−0.640	−3.714	$< \mathbf{10^{-3}}$
	Auto-correlative	α_4	−0.067	−0.461	0.647	−0.029	−0.232	0.818	−0.050	−0.358	0.722
			$R^2_{\text{adj}} = 0.144$			$R^2_{\text{adj}} = 0.164$			$R^2_{\text{adj}} = 0.289$		
75% free	Constant	α_1	0.006	0.116	0.908	0.209	0.710	0.481	0.597	1.444	0.156
	Trend	α_2	−0.001	−1.103	0.276	−0.002	−2.489	0.017	−0.007	−2.869	**0.006**
	Stationarity	α_3	0.018	0.161	0.873	−0.042	−0.537	0.594	−0.109	−1.228	0.226
	Auto-correlative	α_4	−0.264	−1.513	0.137	−0.216	−1.409	0.166	−0.145	−1.201	0.236
			$R^2_{\text{adj}} = 0.054$			$R^2_{\text{adj}} = 0.096$			$R^2_{\text{adj}} = 0.158$		
100% free	Constant	α_1	0.198	1.656	0.105	1.360	2.354	0.023	1.098	1.846	0.072
	Trend	α_2	0.0004	0.926	0.359	0.002	1.275	0.209	−0.004	−1.876	0.067
	Stationarity	α_3	−0.254	−1.582	0.121	−0.340	−2.311	0.026	−0.209	−1.757	0.086
	Auto-correlative	α_4	−0.225	−1.256	0.216	0.052	0.373	0.711	−0.074	−0.608	0.547
			$R^2_{\text{adj}} = 0.132$			$R^2_{\text{adj}} = 0.077$			$R^2_{\text{adj}} = 0.094$		

Extended Data Table 1 Time series model for prisoner's dilemma and trust game. We fitted equation $C_t - C_{t-1} = \alpha_1 + \alpha_2 t + \alpha_3 C_{t-1} + \alpha_4(C_{t-1} - C_{t-2}) + \epsilon_t$ to the data displayed in Extended Data Fig. 2A and 2B, where α_i, $i = 1, 2, 3, 4$ are the regression coefficients, and ϵ_t is a normally distributed error term with a zero mean and an unknown variance. The regression coefficients have the following interpretation: α_1 is a constant term, $\alpha_2 \neq 0$ indicates trend, $\alpha_3 < 0$ indicates stationarity, and $\alpha_4 \neq 0$ indicates auto-correlation. The results show that while the small negative trend is predominant, it becomes slightly positive in entirely free populations of players for the cooperation frequency and entrusted amount. The trends are, however, rarely significant. There is no significant auto-correlation, but stationarity stops being significant in treatments with high and entirely free populations of players.

			Ultimatum game								
			Proposed			**Accepted**			**Rejected**		
Summary (*model*)	Coefficients		Estimate	t-statistic	p-value	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
0% free	Constant	α_1	1.178	5.318	**$< 10^{-5}$**	0.957	3.307	**0.002**	0.262	3.214	**0.002**
	Trend	α_2	-0.003	-5.766	**$< 10^{-6}$**	-0.001	-0.818	0.418	-0.004	-3.007	**0.004**
	Stationarity	α_3	-0.354	-5.193	**$< 10^{-5}$**	-0.338	-3.210	**0.002**	-0.544	-3.368	**0.002**
	Auto-correlative	α_4	-0.195	-1.67	0.102	-0.020	-0.158	0.876	-0.047	-0.342	0.734
			$R^2_{\text{adj}} = 0.413$			$R^2_{\text{adj}} = 0.167$			$R^2_{\text{adj}} = 0.248$		
25% free	Constant	α_1	1.821	3.314	**0.002**	2.581	4.695	**$< 10^{-4}$**	0.181	3.687	**$< 10^{-3}$**
	Trend	α_2	-0.004	-3.20	**0.003**	-0.002	-3.284	**0.002**	-0.003	-3.162	**0.003**
	Stationarity	α_3	-0.586	-3.329	**0.002**	-0.917	-4.672	**$< 10^{-4}$**	-0.624	-4.152	**$< 10^{-3}$**
	Auto-correlative	α_4	-0.177	-1.318	0.194	0.032	0.217	0.830	0.049	0.341	0.734
			$R^2_{\text{adj}} = 0.350$			$R^2_{\text{adj}} = 0.432$			$R^2_{\text{adj}} = 0.287$		
50% free	Constant	α_1	2.535	3.626	**$< 10^{-3}$**	2.349	3.126	**0.003**	0.107	3.026	**0.004**
	Trend	α_2	-0.009	-3.643	**$< 10^{-3}$**	-0.006	-3.386	**0.002**	-0.001	-2.360	0.023
	Stationarity	α_3	-0.784	-3.655	**$< 10^{-3}$**	-0.784	-3.119	**0.003**	-0.478	-3.690	**$< 10^{-3}$**
	Auto-correlative	α_4	-0.175	-1.158	0.253	-0.118	-0.666	0.509	-0.208	-1.982	0.054
			$R^2_{\text{adj}} = 0.370$			$R^2_{\text{adj}} = 0.330$			$R^2_{\text{adj}} = 0.300$		
75% free	Constant	α_1	0.712	2.102	0.041	1.051	2.434	0.019	0.144	5.268	**$< 10^{-5}$**
	Trend	α_2	-0.002	-1.617	0.113	-0.003	-2.155	0.037	-0.002	-4.360	**$< 10^{-4}$**
	Stationarity	α_3	-0.217	-2.194	0.034	-0.329	-2.460	0.018	-0.791	-6.213	**$< 10^{-6}$**
	Auto-correlative	α_4	-0.275	-2.167	0.036	-0.198	-1.357	0.182	-0.043	-0.395	0.695
			$R^2_{\text{adj}} = 0.174$			$R^2_{\text{adj}} = 0.189$			$R^2_{\text{adj}} = 0.477$		
100% free	Constant	α_1	1.193	1.969	0.055	2.911	4.035	**$< 10^{-3}$**	0.100	2.491	0.017
	Trend	α_2	-0.002	-2.583	0.013	-0.0004	-0.418	0.678	-0.002	-1.943	0.058
	Stationarity	α_3	-0.330	-1.934	0.060	-0.850	-3.984	**$< 10^{-3}$**	-0.702	-3.591	**$< 10^{-3}$**
	Auto-correlative	α_4	-0.057	-0.280	0.781	-0.022	-0.136	0.893	-0.279	-1.981	0.054
			$R^2_{\text{adj}} = 0.100$			$R^2_{\text{adj}} = 0.353$			$R^2_{\text{adj}} = 0.494$		

Extended Data Table 2 Time series model for ultimatum game. We fitted equation $C_t - C_{t-1} = \alpha_1 + \alpha_2 t + \alpha_3 C_{t-1} + \alpha_4(C_{t-1} - C_{t-2}) + \epsilon_t$ to the data displayed in Extended Data Fig. 2C, where α_i, $i = 1, 2, 3, 4$ are the regression coefficients, and ϵ_t is a normally distributed error term with a zero mean and an unknown variance. The regression coefficients have the following interpretation: α_1 is a constant term, $\alpha_2 \neq 0$ indicates trend, $\alpha_3 < 0$ indicates stationarity, and $\alpha_4 \neq 0$ indicates auto-correlation. In all cases, the trend is slightly negative, but the results are less frequently significant in treatments with high and entirely free populations of players. There is no auto-correlation, but stationarity stops being significant at high and entirely free populations of proposers.

Appendix A Experiment, instructions, and interface

Ethical approval declarations and preregistration. This study was approved by the Northwestern Polytechnical University Ethics Committee on the use of human participants in research, and carried out in accordance with all relevant guidelines. Informed consent was obtained from all participants. The trust and ultimatum games were preregistered (https://aspredicted.org/KFF_YQK). The prisoner's dilemma game was not included in the preregistration as some data had already been collected by the time the preregistration was submitted.

Experimental Setup. The experiment incorporated three classic games into a network: the Prisoner's Dilemma Game (PDG), the Trust Game (TG), and the Ultimatum Game (UG). Players, positioned on a 7×7 two-dimensional lattice, were randomly designated as either constrained or free. Constrained players had to adopt the same action towards all four neighbours, whereas free players could vary their actions. The proportion of these player types in the network represented the group's decision-making freedom. To augment this freedom, we devised five treatments for each game, each with a different ratio of free players: entirely constrained, 25% free, 50% free, 75% free, and entirely free. In all games, players interacted with their four neighbours over 50 rounds, with their type and neighbours remaining constant. In the PDG, constrained players selected a single strategy for all neighbours, while free players could differentiate their strategies. The TG and UG each consisted of two stages, with the decision-making flexibility differing between constrained and free players only in the first stage. In the TG, each player acted as both trustor and trustee, determining the amount to send and return to neighbours. In the second stage, tokens sent by neighbours were tripled. In the UG, each player served as both proposer and responder, deciding how to distribute and respond to five tokens among their neighbours. Responders could react independently to each neighbour.

Player Recruitment and Implementation. The experimental framework spanned 45 sessions, with the PDG conducted from May 2020 to June 2021, the TG from April to October 2021, and the UG from November to December 2021. Each session involved 49 subjects, and each treatment was conducted over three sessions, resulting in 15 sessions per game (PDG, TG, and UG). We enlisted 2205 undergraduate volunteers from seven universities across north (Shanxi Normal University and Tianjin University of Technology), northwest (Northwestern Polytechnical University, Xijing University, and Xi'an International University), and southwest (Yunnan University and Yunnan University of Finance and Economics) China, with a female representation of 54.3% and an average age of 19.7 years (Table. **??**). Each volunteer participated in one session only, with no repeat participation allowed. To mitigate the effects of known interactions, we ensured that subjects were from different classes and maintained anonymity throughout the experiments. Upon arrival at the computer lab, volunteers were randomly assigned to individual computer cubicles. The experiment's procedures and details were displayed on the computer screen, and formal participation commenced only after volunteers confirmed their understanding of the instructions. Participants played 50 consecutive rounds of games, accruing tokens. The total number of rounds was undisclosed to prevent end-of-treatment effects. For the PDG, the initial endowment was 50 tokens. In each round, players (both constrained and free) had 30 seconds to make a decision using a personalized gameplay interface (Fig. A6). For the TG and UG, the initial endowment was zero tokens, with each player receiving five tokens at the start of each round. Each round comprised two stages. In the TG, during the first stage, each participant, acting as a trustor, decided how many of the five tokens to send to their four neighbours. In the second stage, each participant, now a trustee, decided how many tokens to return to their neighbours. Players (both constrained and free) had 30 seconds to send and return tokens using the personalized gameplay interface, followed by a 30-second review period (Fig. A7-A10). In the UG, during the first stage, each participant, as a proposer, decided how to divide five tokens between themselves and their four neighbours. In the second stage, each participant, now a responder, decided which proposals to accept or reject. Players (both constrained and free) had 30 seconds to propose and respond using the personalized gameplay interface, followed by a 30-second review period (Fig. A11-A14).

The gameplay interface was developed on the o-Tree platform for laboratory, online, and field experiments. Each session lasted approximately 2 hours. As an incentive, the final token tally was converted into a monetary payoff at a rate of RMB 1.0 per token, in addition to a RMB 20 show-up fee. If the token total was negative, the participant received only the show-up fee. At the experiment's conclusion, volunteers verified their payoffs by signing. The average earnings were RMB 443 (ranging from RMB 20 to RMB 1024) for the PDG, RMB 321 (ranging from RMB 20 to RMB 676) for the TG, and RMB 249 (ranging from RMB 91 to RMB 350) for the UG.

Instructions. The English version of the gameplay instructions displayed to participants before the start of the game is presented here. In this translated version, we used the terms *constrained* and *free* to denote player types. However, to avoid framing effects, we used Chinese terms in the original version, which can be translated as *node* and *link* players (see, e.g., Fig. A6 through Fig. A14).

Prisoner's dilemma game

Welcome to our game experiment!

Please read the following instructions carefully. If you encounter any issues during the game, raise your hand, and our expert staff will assist you. This experiment is anonymous; a computer system will assign each participant a random ID number that cannot be traced back to you. Please avoid communicating with other players during the game. The game may last up to 1.5 hours. If you anticipate not staying for the entire duration, please inform us now.

1. Background and objective: This game experiment aims to examine the decision-making patterns of players when faced with binary choices. Each participant will select either strategy A or strategy B to interact with four neighbours. Upon posting your decisions, you will receive a payoff based on the strategies chosen by you and your four neighbours. The payoff matrix is as follows: if both you and your opponent choose strategy A, you will each earn four tokens. If both of you choose strategy B, neither of you earns any tokens. If you and your opponent choose different strategies, the player who chooses strategy A loses two tokens, while the player who chooses strategy B gains six tokens.

$$\begin{array}{cc} & \begin{array}{cc} A & B \end{array} \\ \begin{array}{c} A \\ B \end{array} & \begin{pmatrix} +4 & -2 \\ +6 & 0 \end{pmatrix} \end{array}$$

2. Gameplay rules: During the game, you will be positioned on a two-dimensional lattice and randomly assigned a player type: constrained or free. These player types differ in their strategic flexibility: constrained players choose a single strategy for all neighbours, while free players can select different strategies for each neighbour. The game comprises an undetermined number of rounds. Your total payoff in each round will be the sum of your payoffs from interactions with your four neighbours.

3. Experiment interface: The gameplay uses a custom computer interface comprising a single screen:

- The screen displays your information, the information of your four neighbours, and the results from the preceding round. This includes the strategies you and your neighbours employed and the resulting payoffs. Based on the previous rounds' strategies and outcomes, you must make decisions for the current round within a 30-second timeframe. Upon decision-making, clicking the "Next" button initiates the subsequent round. Failure to press the button within the allotted time results in automatic progression to the next round.

4. Monetary payout: Upon game completion, your final token accumulation is visible. Our staff will

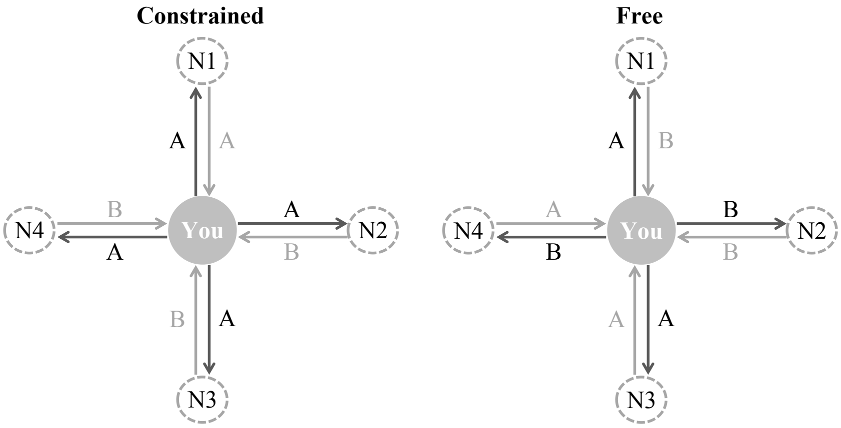


Figure A1 Schematic diagram of gameplay for the prisoner's dilemma game. The constrained player (left) employs the same strategy with all neighbours, while the free player (right) can use different strategies for each neighbour. In this instance, the constrained player adopts strategy A for all neighbours, whereas the free player employs strategy A for neighbours N1 and N3 and strategy B for neighbours N2 and N4. According to the payoff matrix, the cumulative payoffs for the constrained and free players are -2 and eight tokens, respectively.

convert this total into a real monetary payout at a rate of RMB 1 per token. Additionally, a show-up fee of RMB 20 is guaranteed, regardless of your performance.

Trust game

Welcome to our game experiment!

Please read the following instructions carefully. If you encounter any issues during the game, raise your hand, and our expert staff will assist you. This experiment is anonymous; a computer system will assign each participant a random ID number that cannot be traced back to you. Please avoid communicating with other players during the game. The game may last up to two hours. If you anticipate not staying for the entire duration, please inform us now.

1. Background and objective: This game experiment aims to examine player decision-making patterns when tasked with sending and returning tokens amongst themselves. Each player assumes the roles of both trustor (token sender) and trustee (token returner). Initially, you will decide on an amount to send to your four neighbours. Subsequently, you will receive tokens from your neighbours, which will be tripled, and you must decide how many to return. Your payoff is determined by the number of tokens returned by your neighbours and the number you sent.

2. Gameplay rules: During the game, you will be positioned on a two-dimensional lattice and randomly assigned a player type: constrained or free. These types differ in their flexibility in sending tokens to neighbours; constrained players can only send equal amounts to each neighbour, while free players can vary the amounts. Each player starts each round with five tokens. The game comprises an indeterminate number of rounds, each consisting of two stages. In the first stage, as a trustor, you decide how many of the five tokens to retain and how many to send to your neighbours. In the second stage, as a trustee, you receive tokens from your neighbours, which are tripled, and you must decide how many to return. The return amount is equally divided amongst the four neighbours. Thus, as a trustee, your decision affects the entire neighbourhood, not individual neighbours. Your total payoff each round is the sum of the payoffs from the two stages. In the first stage, as a trustor, your payoff is the tokens received from neighbours minus the tokens you sent (Fig. A2). In the second stage, as a trustee, your payoff is the tokens received from neighbours minus the tokens you returned (Fig. A3).

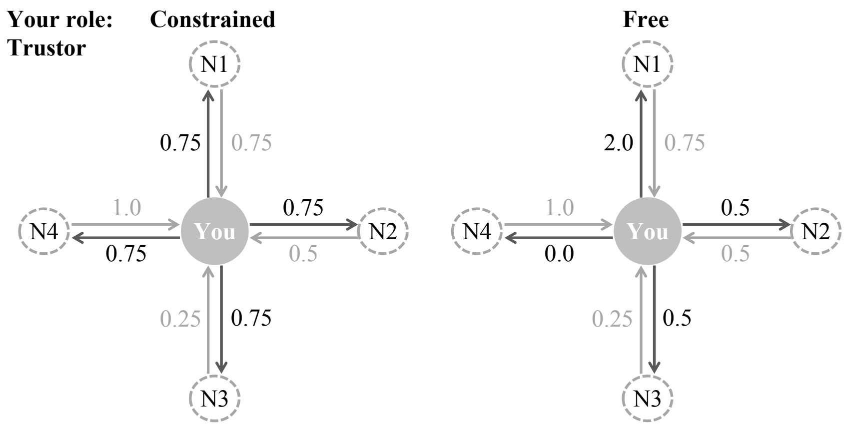


Figure A2 Schematic diagram of gameplay as a trustor. The constrained player (left) can only distribute tokens equally among their neighbours. In this instance, out of five tokens, the constrained player opts to retain two tokens and distribute three tokens among their neighbours. The free player (right) also chooses to retain two tokens and distribute three tokens among their neighbours. However, the free player has the flexibility to decide the number of tokens to send to each individual neighbour.

3. Experiment interface: The gameplay employs a custom computer interface comprising three screens:

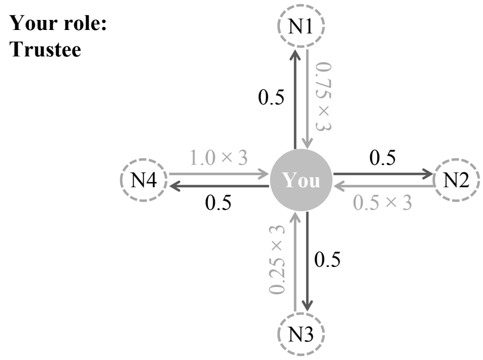


Figure A3 Schematic diagram of gameplay as a trustee. The trustee receives tokens sent by their neighbours after the tokens are multiplied by a compounding factor of 3. The trustee returns 2 tokens to neighbours, which are then equally split between the neighbours, with each neighbour receiving 0.5 tokens.

- On the Trustor screen, you will decide how many of your five tokens to retain and how many to distribute among your four neighbours. As a constrained player, you can enter a value in any one of the four boxes, and the remaining three will automatically display the same value. As a free player, you must input values for each box separately. In both scenarios, the central box displays the total number of tokens you are distributing. If the sum of tokens exceeds five, the system will prompt you to enter a valid amount. You have 30 seconds to complete this stage. Once ready, click the "Next" button to proceed.
- On the trustee screen, you will see the tokens sent by your four neighbours. The central box will display these tokens, multiplied by a factor of three. You must then decide how many tokens to return to your neighbours. Enter a value in any one of the four boxes, and the remaining three will automatically display the same value. The central box shows the total number of tokens you are returning. You have 30 seconds to complete this stage. Once ready, click the "Next" button to proceed.
- On the Result screen, you can review key information for 30 seconds. This includes your actions as a trustor, such as the number of tokens you distributed, the number of tokens returned by your neighbours, and your payoff. It also includes your actions as a trustee, such as the number of tokens received from your neighbours, the number of tokens you returned, and your payoff. The screen will display your balance from the previous and current rounds. After reviewing the results, click the "Next" button to start the next round. If you do not press the button within the allotted time, the system will automatically proceed to the next screen.

4. Monetary payout: Upon the game's conclusion, your final balance will be visible. This balance will be converted into a tangible monetary payout by our staff at a rate of 1 token to RMB 1.0. Additionally, you will receive a participation fee of RMB 20, which is independent of your performance during the experiment.

Ultimatum game

Welcome to our game experiment!

Please read the following instructions carefully. If you encounter any issues during the game, raise your hand, and our expert staff will assist you. This experiment is anonymous; a computer system will assign each participant a random ID number that cannot be traced back to you. Please avoid communicating with other players during the game. The game may last up to two hours. If you anticipate not staying for the entire duration, please inform us now.

1. Background and objective: This game experiment aims to examine players' decision-making patterns when tasked with dividing a sum of tokens between themselves (as proposers) and other players (as responders). Each participant will assume both roles. Initially, you will propose a division of tokens between yourself and your four neighbours. Subsequently, you will respond to your neighbours' proposals by either accepting or rejecting them. The payoff you receive will depend on the responses to your proposal and your reactions to your neighbours' proposals.

2. Gameplay rules: During the game, you will be positioned on a two-dimensional lattice and randomly assigned as either a constrained player or a free player. These player types differ in their ability to divide a sum of tokens among their neighbours. Constrained players can only distribute tokens equally among the neighbours, while free players have the flexibility to allocate tokens differently for each neighbour. Each round provides each player with an endowment of five tokens. The game comprises an indeterminate number of rounds, each consisting of two stages. In the first stage, you act as a proposer and decide how to divide five tokens between yourself and your four neighbours. In the second stage, you act as a responder, receiving offers from four neighbours and deciding which proposals to accept or reject.

Your total payoff in each round will be the sum of payoffs from the two stages. In the proposal stage, you will receive a payoff only if your neighbours accept your proposal (Fig. A4). In the responder stage, you will receive a payoff only from the proposals you decide to accept (Fig. A5).

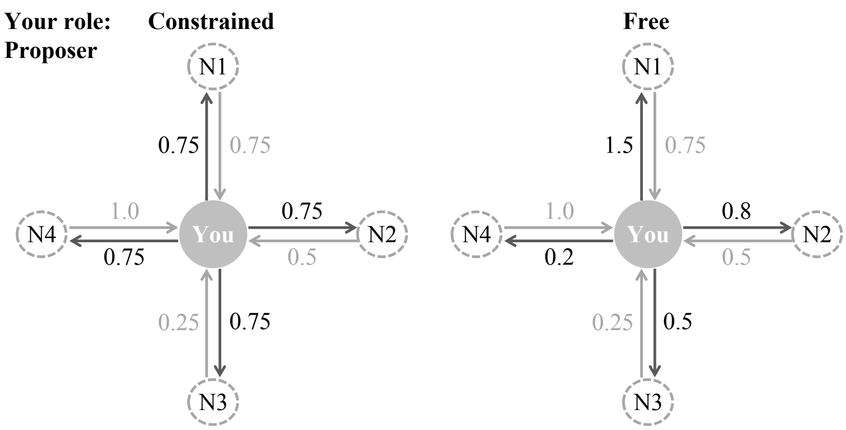


Figure A4 Schematic diagram of gameplay as a proposer. The constrained player (left) can only distribute tokens equally among neighbours. In this instance, the player proposes to retain two out of five tokens and distribute the remaining three equally. The free player (right) also proposes to keep two tokens but has the flexibility to distribute the remaining tokens among neighbours individually. The tokens retained by the proposer are divided by four (the number of neighbours), and the proposer receives a payoff only from neighbours who accept the proposal. If a proposal is rejected, both the proposer and neighbour receive no payoff. For instance, if three neighbours accept the offer in our diagram, the proposer receives $2 \times 3/4 = 1.5$ tokens. If two neighbours accept the offer, the payoff is $2 \times 2/4 = 1$, and so on.

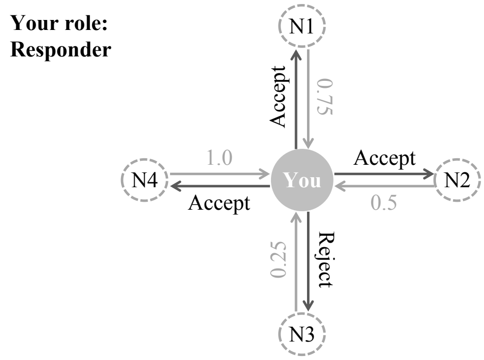


Figure A5 Schematic diagram of gameplay as a responder. The focal responder receives proposals from four neighbours, N1-4, and decides which to accept or reject. In this example, the responder accepts proposals from neighbours N1, N2, and N4, and rejects the offer from neighbour N3. Consequently, the total payoff received by the focal responder is $0.75+0.5+1 = 2.25$.

3. Computer interface: The gameplay employs a custom computer interface comprising three screens:

- On the proposer screen, you are tasked with distributing five tokens amongst yourself and four neighbours. As a constrained player, you can assign a value to any one of the four boxes, and the remaining three will automatically display the same value. As a free player, you must individually assign values to each of the four boxes. In both scenarios, a central box will display the total number of tokens you propose to distribute amongst your neighbours. If your proposal exceeds five tokens, the system will prompt you to submit a valid proposal. You have 30 seconds to complete this stage. Once ready, click the "Next" button to proceed.
- On the responder screen, you will view proposals from your four neighbours. For each proposal, you must decide whether to accept or reject the offer within a 30-second timeframe. Once you have made your decisions, click the "Next" button to advance.
- The result screen allows you to review key information for a duration of 30 seconds. This includes your actions as a proposer: your proposal to four neighbours, their responses, the acceptance status of your proposal, and your payoff. As a responder, you can view the proposals of your four neighbours, their acceptance status, and your payoff. The screen also displays your endowment balance from the previous round and the current round. After reviewing the results, click the "Next" button to initiate the next round. Failure to press the button within the specified time will result in the system automatically progressing to the next screen.

4. Monetary payout: Upon game completion, you can view your final balance. Our staff will convert this balance into a real monetary payout at a rate of RMB 1 per token. Additionally, you will receive a show-up fee of RMB 20, regardless of your performance during the experiment.

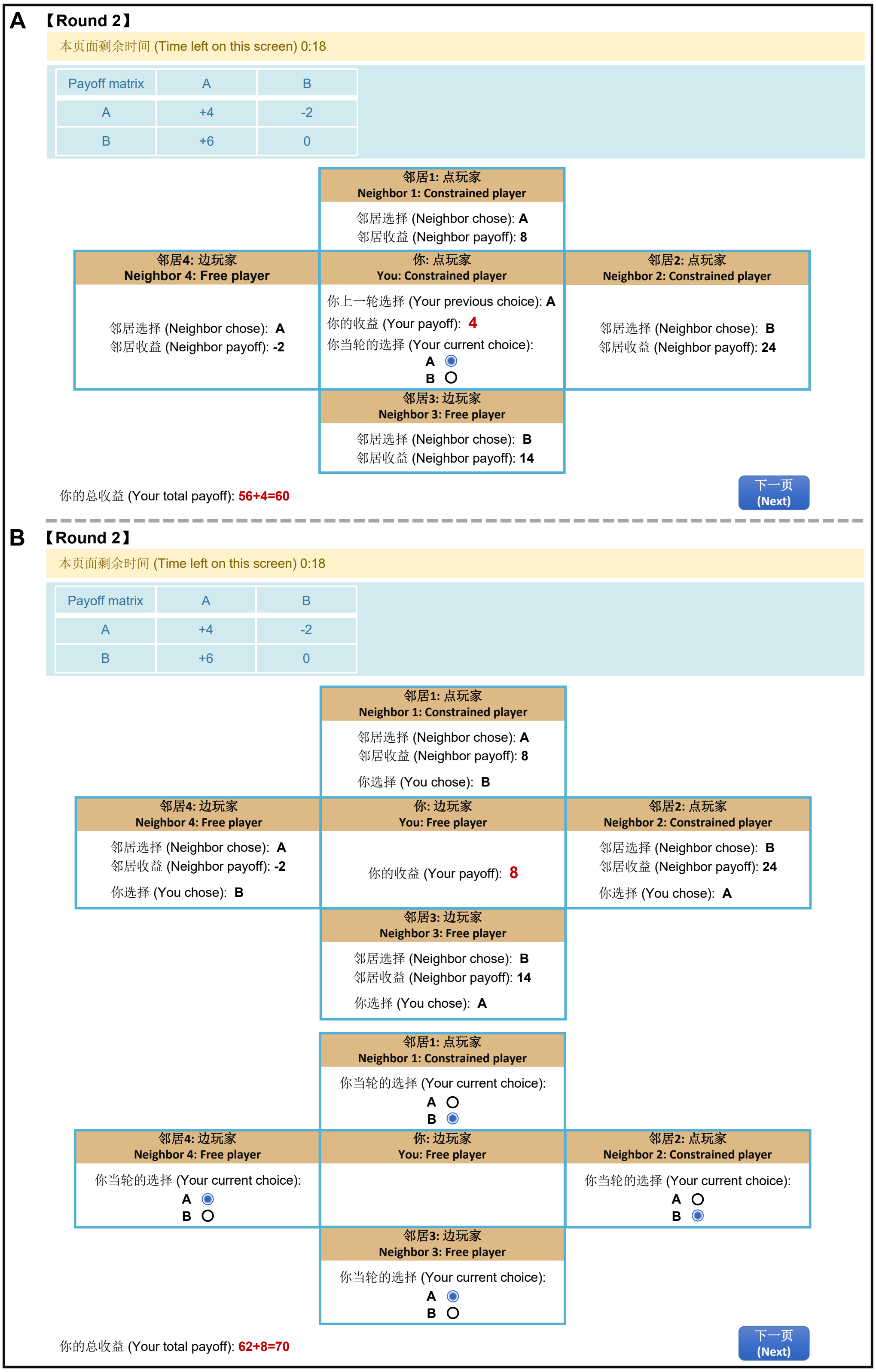


Figure A6 Constrained and free players' interface in the prisoner's dilemma game.

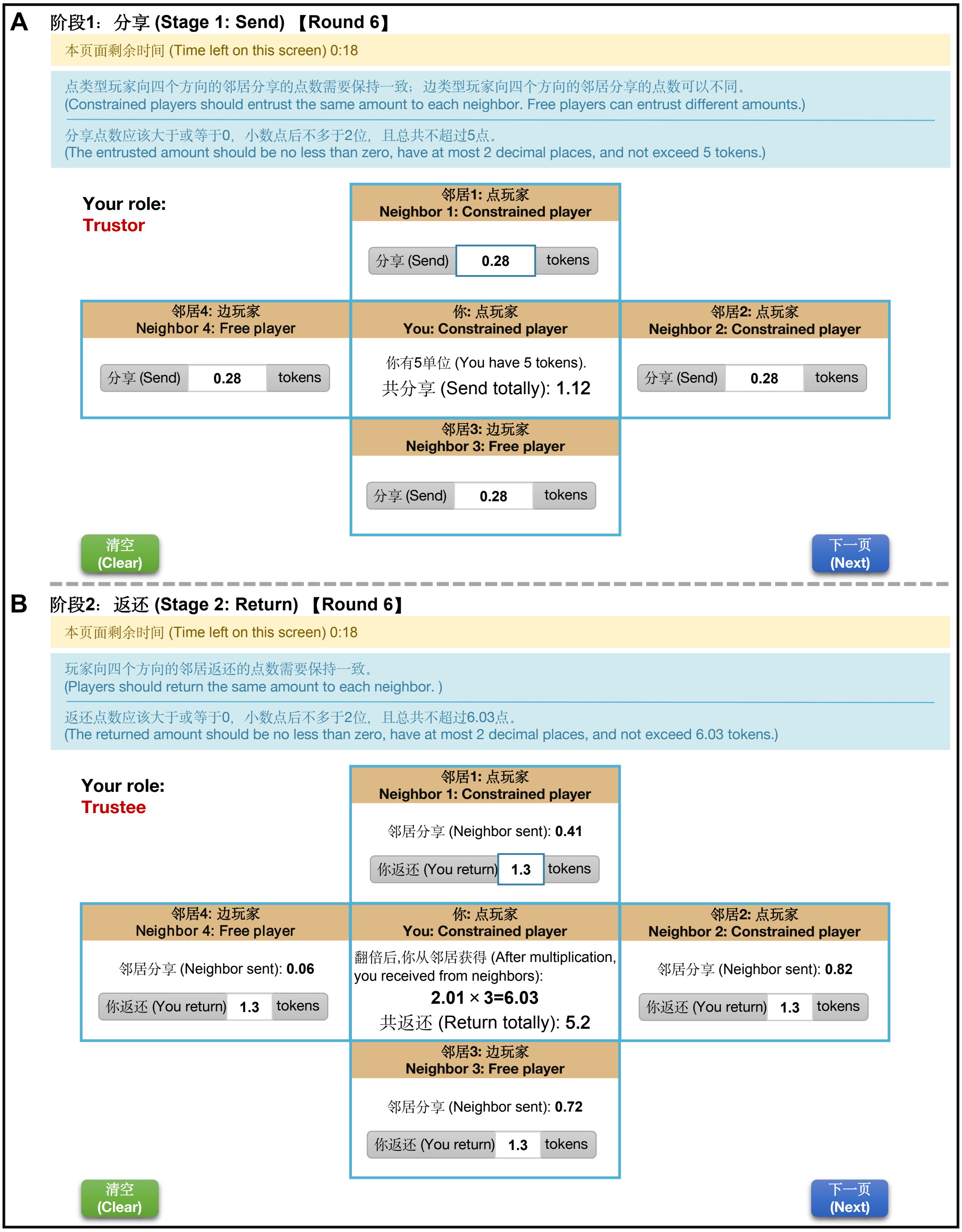


Figure A7 Constrained trustor and trustee's interface in the trust game.

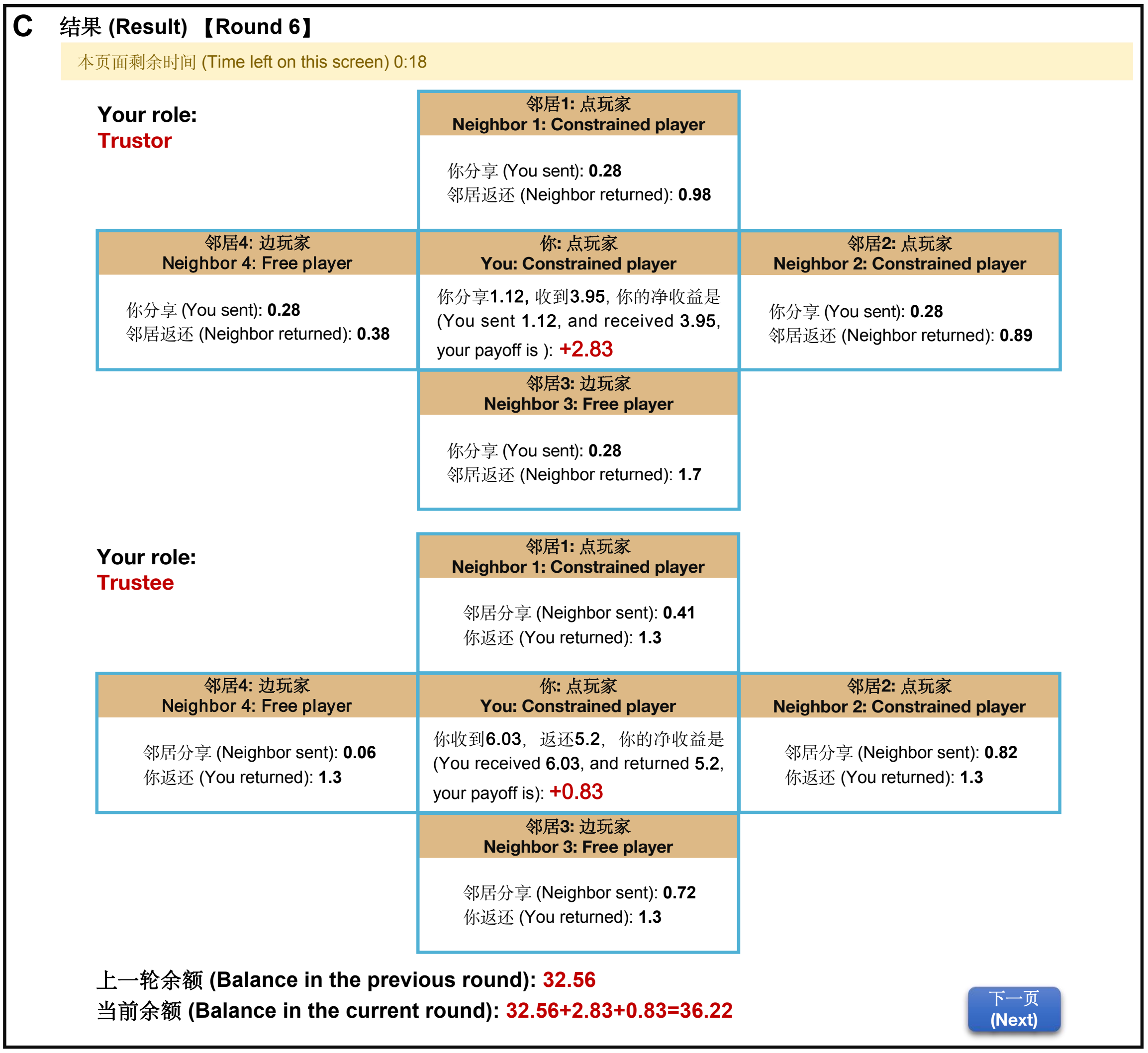


Figure A8 Constrained player's result interface in the trust game.

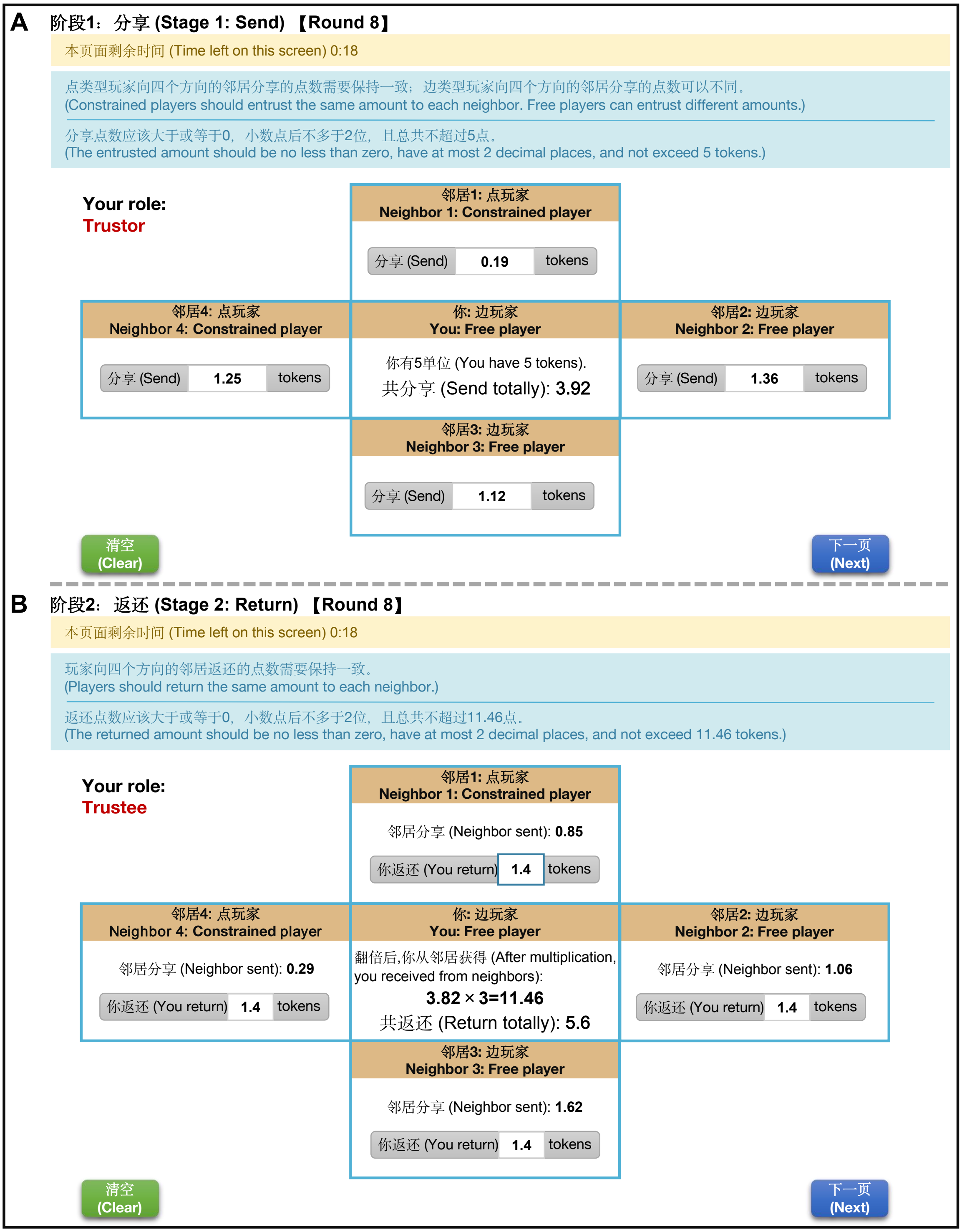


Figure A9 Free trustor and trustee's interface in the trust game.

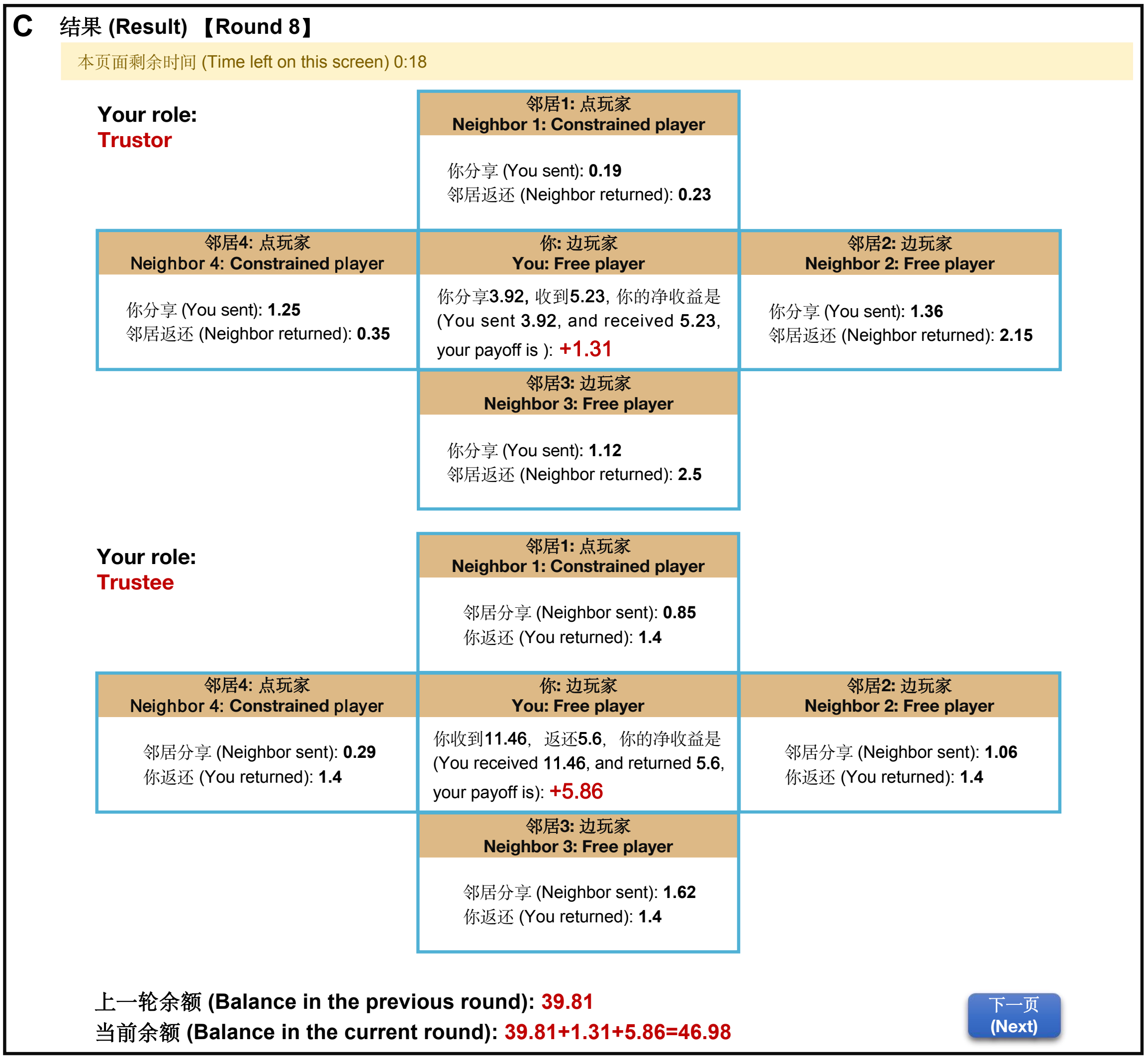


Figure A10 Free player's result interface in the trust game.

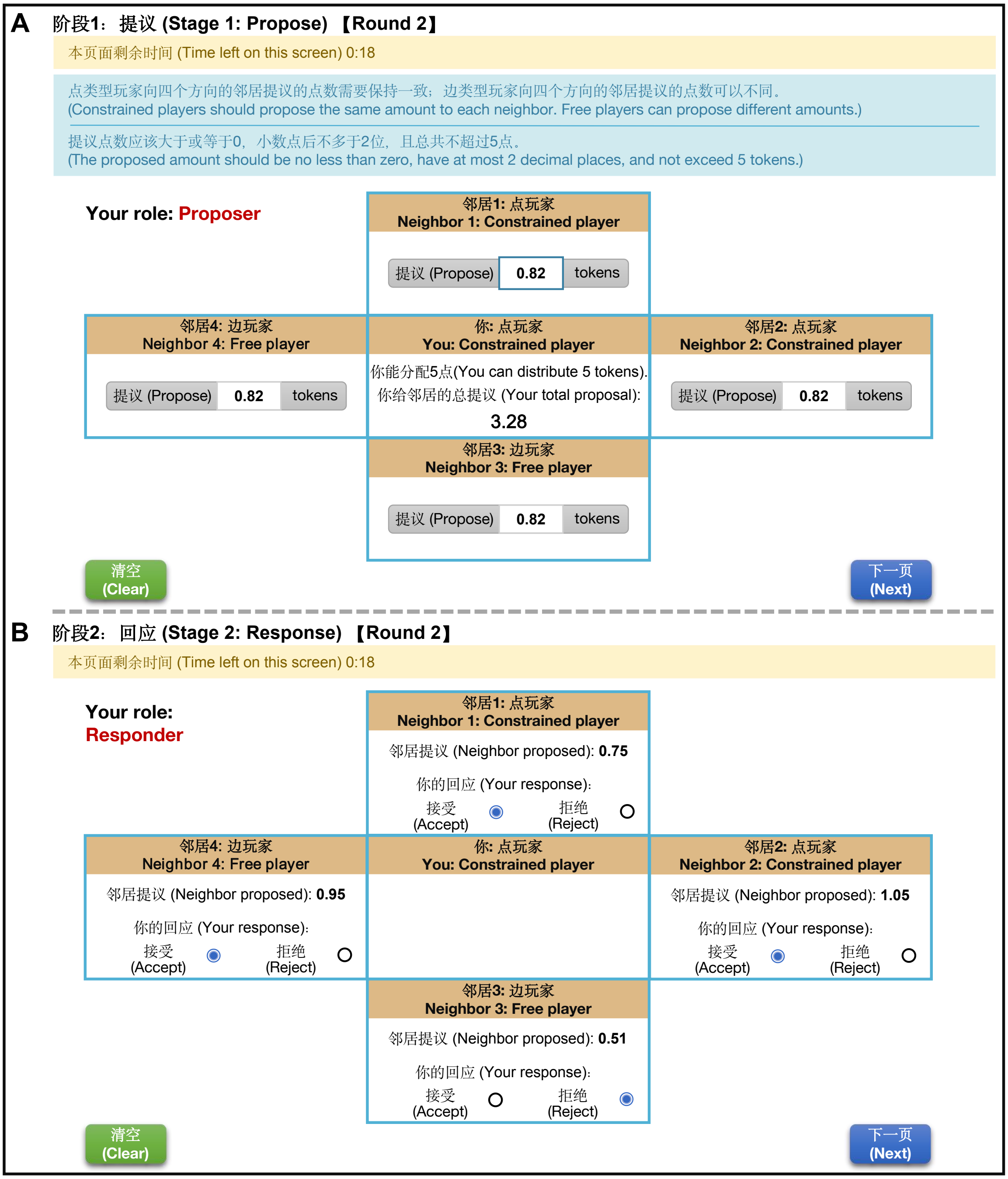


Figure A11 Constrained proposer and responder's interface in the ultimatum game.

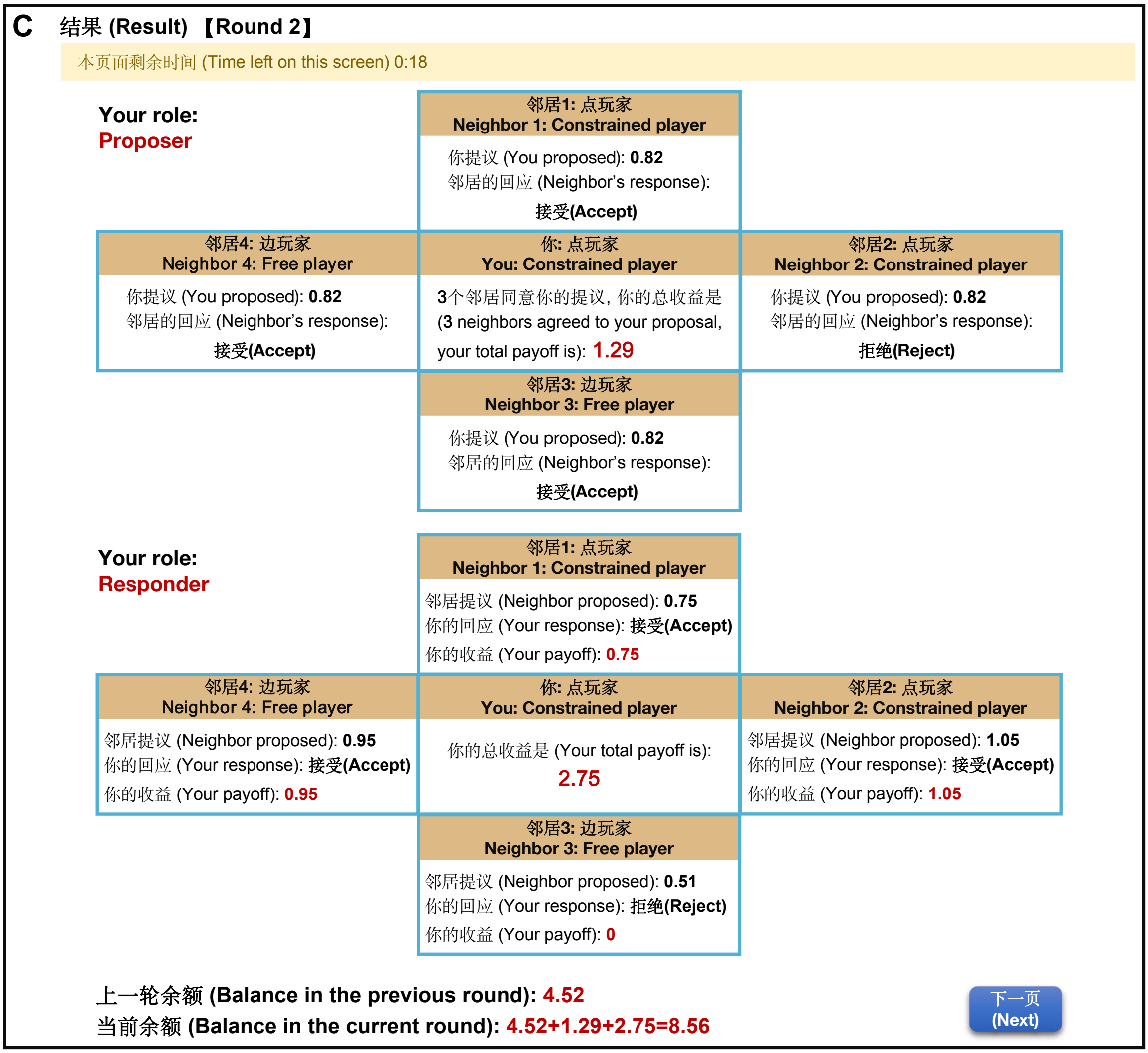


Figure A12 Constrained player's result interface in the ultimatum game.

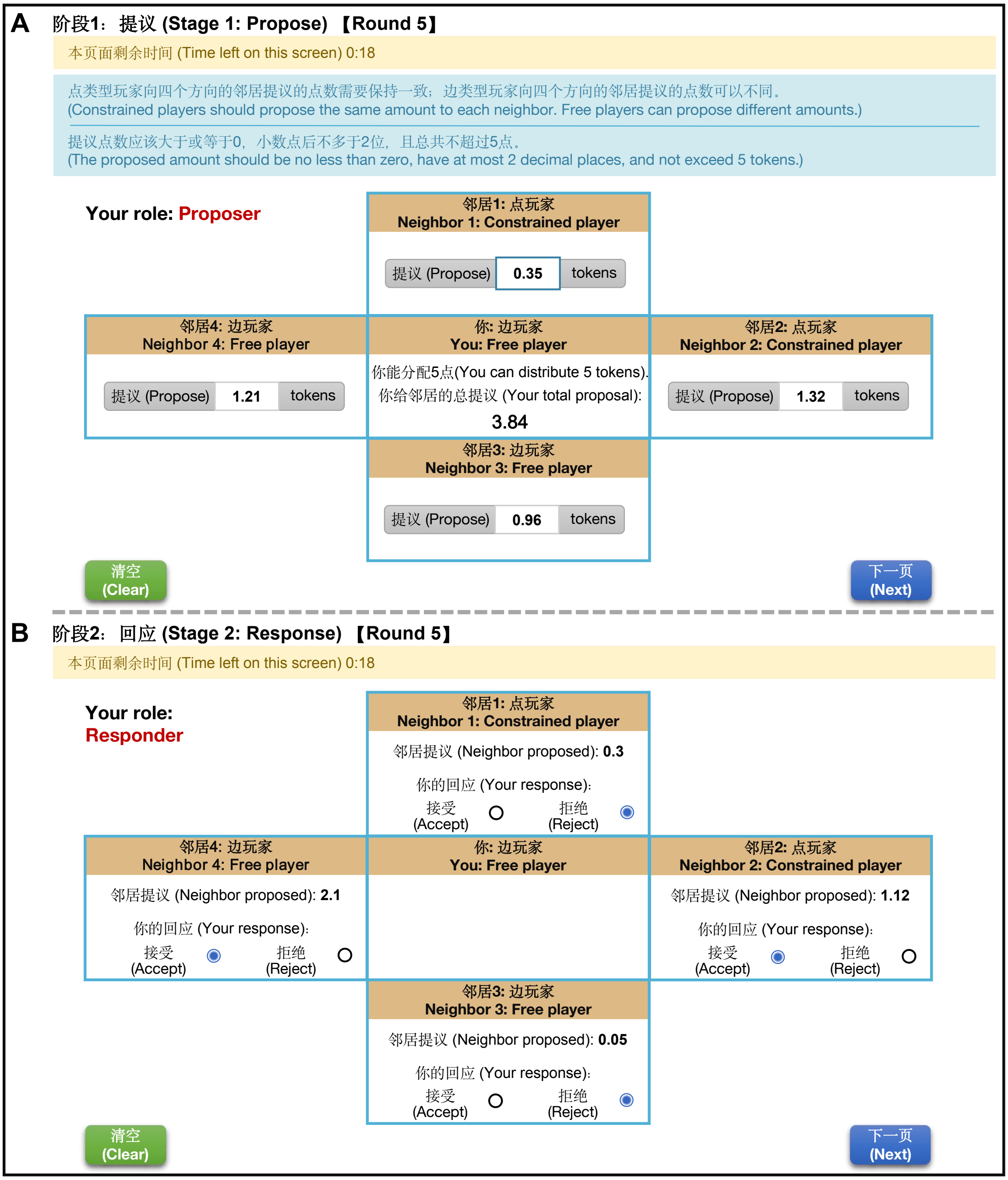


Figure A13 Free proposer and responder's interface in the ultimatum game.

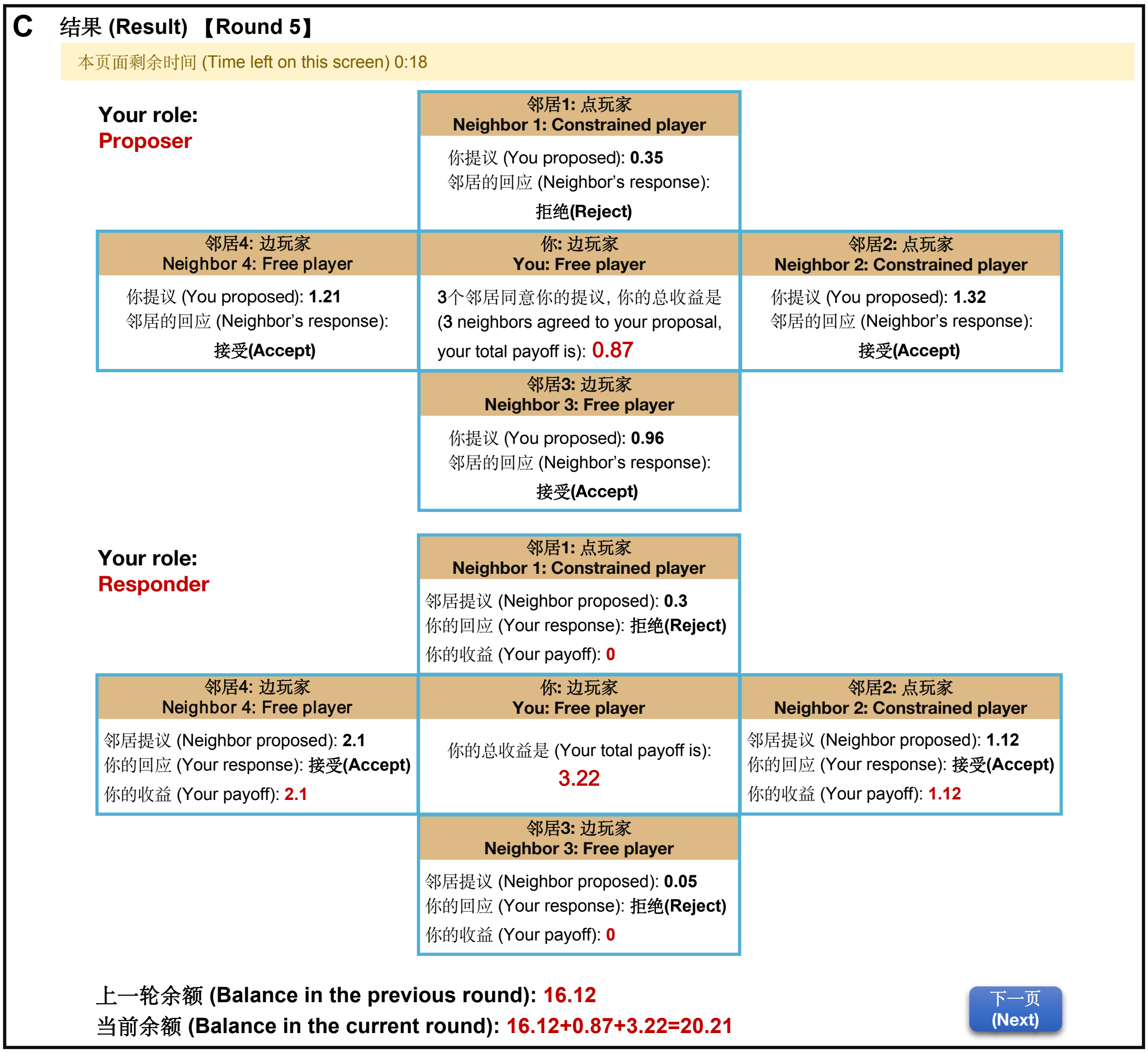


Figure A14 Free player's result interface in the ultimatum game.

Appendix B Cluster analysis

We conducted a cluster analysis to identify behavioural phenotypes across three economic games. For each game, we extracted six behavioral variables as clustering factors based on players' overall performance and their responses to previous rounds. In the trust and ultimatum games, where individuals assume different roles in two stages—trustor and proposer in the first, and trustee and responder in the second—we conducted separate analyses for each stage. The analysis used the K-means clustering algorithm, and the optimal number of clustering categories was determined using the Nbclust package in R.

B.1 Cluster analysis for the prisoner's dilemma and the first stage of the trust and ultimatum games

For the prisoner's dilemma game, we chose six clustering factors based on the overall cooperation frequency and the probability of cooperating in response to the previous round's circumstances. The clustering factors A-F are as follows:

A cooperation frequency;
B probability of playing C after focal player played C in the previous round;
C probability of playing C after focal player played D in the previous round;
D probability of playing C after up to one neighbour played C;
E probability of playing C after exactly two neighbours played C;
F probability of playing C after at least three neighbours played C.

For the first stage of the trust game, we define six clustering factors based on the average overall entrusted amount and the average entrusted amount in response to the previous round's circumstances. The clustering factors A-F of population as trustor in the trust game are as follows:

A entrusted amount;
B entrusted amount after the trustor sent four or more in the previous round;
C entrusted amount after the trustor sent less than four in the previous round;
D entrusted amount when up to one neighbouring trustee returned an amount equal to or greater than the trustor's previous send;
E entrusted amount when exactly two neighbouring trustees returned an amount equal to or greater than the trustor's previous send;
F entrusted amount when at least three neighbouring trustees returned an amount equal to or greater than the trustor's previous send.

For the first stage of the ultimatum game, we define six clustering factors based on the average overall proposed amounts and the average proposed amounts in response to the previous round's circumstances. The clustering factors A-F of population as proposer are as follows:

A proposed amount;
B proposed amount after the proposer sent four or more in the previous round;
C proposed amount after the proposer sent less than four in the previous round;
D proposed amount when up to two neighbouring responders accept the proposal in the previous round;
E proposed amount when exactly three neighbouring responders accept the proposal in the previous round;
F proposed amount when exactly four neighbouring responders accept the proposal in the previous round.

For the K-means clustering algorithm, the number of clusters must be specified in advance. We used Dindex, a graphical method, to determine the optimal number of clusters. In the Dindex graph generated by the Nbclust package using the 'euclidean' distance and the 'kmeans' method in the R programming language, the optimal number of clusters is identified at the point where the graph shows a sharp knee shape. This peak indicates a substantial increase in the measure's value, signaling the most suitable cluster count for the data analysis.

The Dindex method suggests that the optimal number of clusters for the prisoner's dilemma is four (Fig. B15 A). For the first stages of the trust game and the ultimatum game, the optimal numbers of clusters are three each (Fig. B15 B, C). Additionally, we also used the SDindex method, which found that the optimal number of clusters for the prisoner's dilemma is three (Subgraph of Fig. B15 A). Considering these findings, we determined the number of clusters for the prisoner's dilemma and the first stage of the trust and ultimatum games to be three.

In summary, for the prisoner's dilemma game and the first stage of the trust and ultimatum games, the K-means clustering algorithm was implemented with three clusters based on six clustering factors for each game. The results are displayed in Fig. 3.

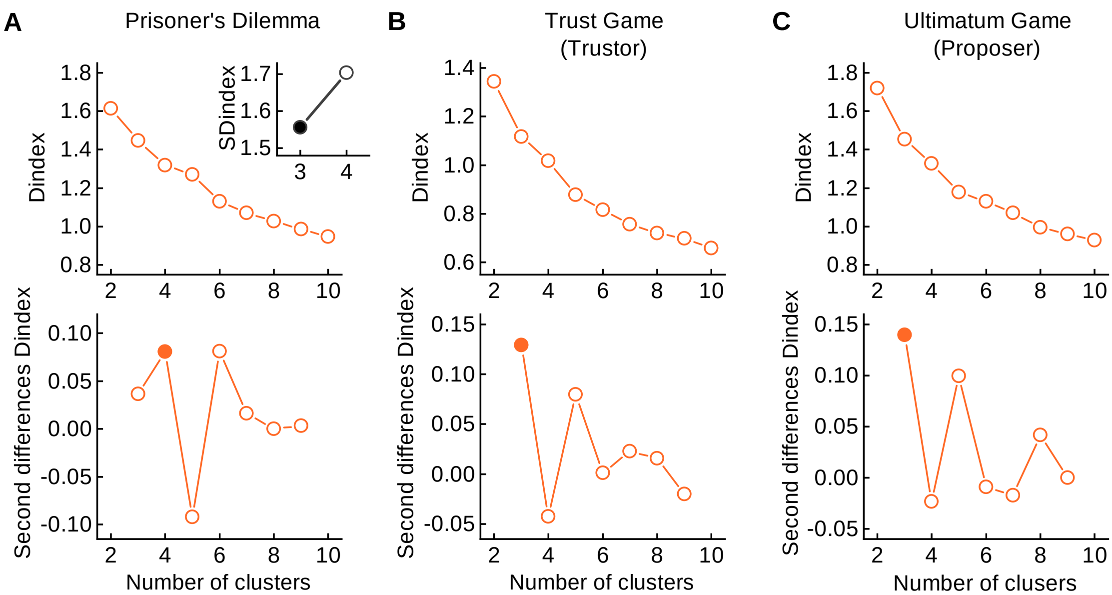


Figure B15 The optimal number of clusters for the prisoner's dilemma and the first stage of the trust and ultimatum games.

B.2 Cluster analysis for the second stage of the trust and ultimatum games

For the second stage of the trust and ultimatum games, we conducted cluster analysis to identify the behavioural phenotypes within the population, focusing on the trustee's returned amount and the responder's accepted amount.

In the second stage of the trust game, we define six clustering factors based on the average overall returned amounts and the average returned amounts in response to the previous round's circumstances. The clustering factors A-F of population as trustee are as follows:

A returned amount;
B returned amount after the trustee received four or more in the previous round;

C returned amount after the trustee received four or more in the previous round;
D returned amount after up to one neighbouring trustor sent an amount equal to or greater than in the previous round;
E returned amount after exactly two neighbouring trustors sent an amount equal to or greater than in the previous round;
F returned amount after at least three neighbouring trustors sent an amount equal to or greater than in the previous round.

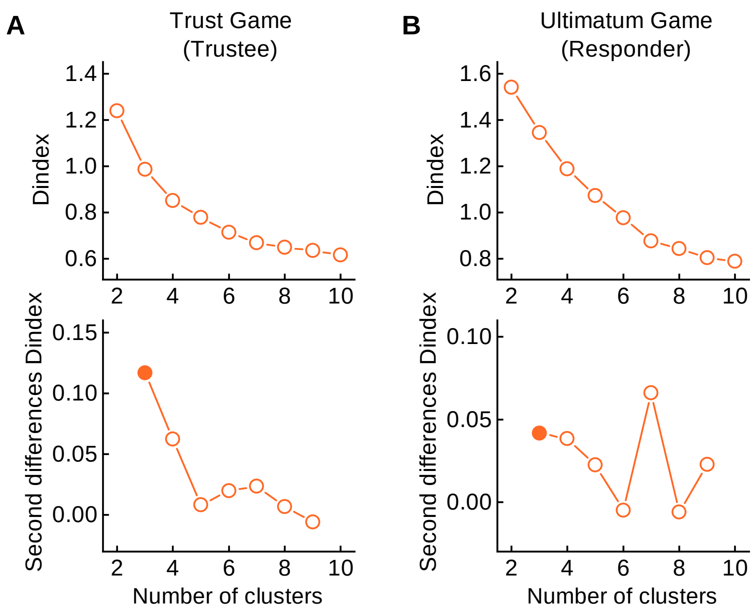


Figure B16 The optimal number of clusters for trustee in the trust game and responder in the ultimatum game.

In the second stage of the ultimatum game, we define six clustering factors based on the average overall accepted amount and the average accepted amount in response to the previous round's circumstances. The clustering factors A-F of population as responder are as follows:

A accepted amount;
B accepted amount after receiving a total offer of four or more in the previous round;
C accepted amount after receiving a total offer of less than four in the previous round;
D accepted amount when up to two neighbouring proposers propose an amount equal to or greater than in the previous round;
E accepted amount when exactly three neighbouring proposers propose an amount equal to or greater than in the previous round;
F accepted amount when exactly four neighbouring proposers propose an amount equal to or greater than in the previous round.

According to Dindex method, the optimal number of clusters in the second stage of the trust and ultimatum games is three for each (Fig. B16 B).

The K-means clustering algorithm was implemented with three clusters for both the trustee role in the trust game and the responder role in the ultimatum game, based on six clustering factors for each role. The results are displayed in Extended Data Fig. 4.

B.3 Behaviour consistency analysis across different stages of the trust and ultimatum games

For the trust game and the ultimatum game, cluster analysis was conducted independently for each stage. To evaluate consistency in players' behaviors across stages, we also analyzed the behavioural phenotypes—prosocial, neutral, and antisocial—identified from the first stage's clustering results, in the subsequent stage. Specifically, in the trust game, we examined the returned amounts by prosocial, neutral, and antisocial groups (from the first stage as trustors) during the second stage (as trustees) using six clustering factors (Extended Data Fig. 5 A). A similar approach was used in the ultimatum game for the accepted amounts by these groups (from the first stage as proposers) during the second stage (as responders), as shown in Extended Data Fig. 5 B. This analysis confirms that player behaviors remain consistent across stages; for instance, those categorized as prosocial in the first stage continue to exhibit prosocial behaviors in the second stage, and the same holds for neutral and antisocial groups.

Appendix C Model analysis

C.1 Prisoner's dilemma

C.1.1 Numerical simulation

To perform the numerical simulation based on the model delineated in the Methods section, we derived probabilities for agents' initial strategies and strategy updating from experimental data (an overview of variables is in Table **??**). We denoted probabilities as (p^c; $p^c_{Ck_C}, p^c_{Dk_C}$) for constrained agents and (p^f; p^f_C, p^f_D) for free agents.

Initial strategies. For the agents' initial strategy, we assumed that the probability that agents choose to cooperate is related to the behaviour of neighbours. Therefore, based on the experimental data from the first round, for free and constrained agents, we calculated their proportion of cooperation, denoted as p^f and p^c, respectively. Therefore, at time $t = 0$, towards a neighbour j cooperated (i.e., $s_{ij} = 1$) with probability p^f and defected (i.e., $s_{ij} = 0$) otherwise. Agent i with $v_i = 0$ cooperated with probability p^c (i.e., $s_{ij} = 1$ for all $j \in \mathcal{N}_i$; the set of i's neighbours) and defected otherwise.

Strategy updating. In the strategy updating process, we assumed that the free agent i's (i.e., $v_i = 1$) strategy towards neighbour j at time $t+1$ was determined by the neighbour j's strategy s_{ji} at time t. The constrained agent i's (i.e., $v_i = 0$) strategy s_{ij} towards neighbour $j \in \mathcal{N}_i$ (the set of i's neighbours) at time $t+1$ was determined by agent i's strategy and the number of cooperative neighbours k_C ($k_C = 0, 1, 2, 3, 4$).

Free agent i updated their strategy towards neighbour j as below.
(i) For $s_{ji} = 1$ at time t, agent i chose strategy $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability p^f_C (resp. $1 - p^f_C$) at time $t + 1$;
(ii) For $s_{ji} = 0$ at time t, agent i chose strategy $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability p^f_D (resp. $1 - p^f_D$) at time $t + 1$;

Constrained agent i updated their strategy towards neighbour $j \in \mathcal{N}_i$ as below.
(i) For $s_{ij} = 1$, if k_C neighbours of agent i chose strategy $s_{ji} = 1$ at time t, agent i chose strategy $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability $p^c_{Ck_C}$ (resp. $1 - p^c_{Ck_C}$) at time $t + 1$;
(ii) For $s_{ij} = 0$, if k_C neighbours of agent i chose strategy $s_{ji} = 1$ at time t, agent i chose strategy $s_{ij} = 1$ (resp. $s_{ij} = 0$) with probability $p^c_{Dk_C}$ (resp. $1 - p^c_{Dk_C}$) at time $t + 1$;

Notably, in each time step, free agents independently updated their strategy against each neighbour according to the aforementioned rules. In contrast, constrained agents updated their strategy towards the entire neighbourhood.

Initialization. The simulation was initialized with constrained and free agents randomly distributed on an $L \times L$ square lattice with a periodic boundary and a von Neumann neighbourhood. The fraction of free agents was denoted by F, where a set of $F = 0.00 : 0.05 : 1.00$ was investigated. Each agent engaged in a repeated PDG with their neighbours and accumulated a payoff based on the same payoff matrix as the experiment. For a complete Monte Carlo simulation, we observed the cooperation frequency and the average payoff on the lattice of size $L = 100$ over 10^4 time steps, of which the last 2×10^3 has up to a stable state. All results were averaged over 1000 independent realizations for a fixed set of free agent densities.

C.1.2 Theoretical analysis

Our analysis assumes that one's action updating depends on one's joint action profile last round rather than the comparison of participants' payoffs. Let $\rho^f(t)$ (resp. $\rho^c(t)$) denote the cooperation frequency of free (resp. constrained) players at time t. Here we adopt the mean-field approach to approximate the change in $\rho^f(t)$ and $\rho^c(t)$.

The change in the cooperation frequency of free players, i.e., $\rho^f(t)$, is

$$\begin{aligned} d_t\rho^f(t) = \left(1-\rho^f(t)\right) &\begin{pmatrix} \left(F\rho^f(t)+(1-F)\rho^c(t)\right)p_C^f \\ +\left(F(1-\rho^f(t))+(1-F)(1-\rho^c(t))\right)p_D^f \end{pmatrix} \\ -\rho^f(t) &\begin{pmatrix} \left(F\rho^f(t)+(1-F)\rho^c(t)\right)(1-p_C^f) \\ +\left(F(1-\rho^f(t))+(1-F)(1-\rho^c(t))\right)(1-p_D^f) \end{pmatrix}. \end{aligned} \tag{C1}$$

The probability that a constrained player has k_C cooperative neighbours is

$$\begin{aligned} \mathcal{C}(k_C) =& \frac{k!}{k_C!(k-k_C)!}\left(F\rho^f(t)+(1-F)\rho^c(t)\right)^{k_C} \\ & \left(1-F\rho^f(t)-(1-F)\rho^c(t)\right)^{k-k_C}, \end{aligned} \tag{C2}$$

The change in the cooperation frequency of constrained players, i.e., $\rho^c(t)$, is

$$d_t\rho^c(t) =(1-\rho^c(t))\sum_{k_C=0}^{k}\mathcal{C}(k_C)p_{Dk_C}^c - \rho^c(t)\sum_{k_C=0}^{k}\mathcal{C}(k_C)(1-p_{Ck_C}^c). \tag{C3}$$

The cooperation frequency of the population is

$$\rho_C =F\rho^f + (1-F)\rho^c. \tag{C4}$$

The accumulated payoff of one player is

$$\begin{aligned} Q =& kF\begin{pmatrix} F\rho^{2f}rw+F\rho^f(1-\rho^f)sp \\ +F(1-\rho^f)\rho^f tm+F(1-\rho^f)^2pn \\ +(1-F)\rho^f\rho^c rw+(1-F)\rho^f(1-\rho^c)sp \\ +(1-F)(1-\rho^f)\rho^c tm+(1-F)(1-\rho^f)(1-\rho^c)pn) \end{pmatrix} \\ &+k(1-F)\begin{pmatrix} F\rho^c\rho^f rw+F\rho^c(1-\rho^f)sp \\ +F(1-\rho^c)\rho^f tm+F(1-\rho^c)(1-\rho^f)pn \\ +(1-F)\rho^{2c}rw+(1-F)\rho^c(1-\rho^c)sp \\ +(1-F)(1-\rho^c)\rho^c tm+(1-F)(1-\rho^c)^2pn \end{pmatrix}. \end{aligned} \tag{C5}$$

where rw, sp, tm, pn respectively correspond to the payoff under mutual cooperation, unilateral cooperation, unilateral defection, and mutual defection.

C.2 Trust game

C.2.1 Numerical simulation

To perform the numerical simulation based on the model outlined in the Methods section of the paper, we inferred several aspects of the agents' behaviour from the experimental data (Table **??** presents the variables overview). For the entrusted amount in the first stage of the game, we discretized the continuous strategy space in a manner similar to the cooperation and defection strategies in the prisoner's dilemma game. Specifically, we used the average entrusted amount of agents in the trust game as the critical threshold for interval division. If an agent's entrusted amount exceeded the average, their decision was classified as belonging to the prosocial preference interval; otherwise, it was classified as belonging to the antisocial preference interval. After statistical analysis, the average entrusted amount was calculated to be 0.75, leading us to define two entrusted amount intervals for the trust game $S = \{S_1, S_2\}$, where $S_1 \in [0, 0.75)$, and $S_2 \in (0.75, 5.0]$. Constrained and free agents updated their strategies in the first stage following (p^c_x; $p^c_{x,y}$) and (p^f_x; $p^f_{x,y}$) response rules; in the second stage of the game, they followed a fixed return ratio of λ_c and λ_f respectively. Therefore, the specific values corresponding to p^c_x, $p^c_{x,y}$, p^f_x, $p^f_{x,y}$, λ_c, and λ_f were also inferred from the experimental data.

Initial strategies. For the agents' entrusted amount in the first round, we inferred from the data the frequency of the constrained agents' entrusted amount in intervals S_1 and S_2, respectively, denoted as $\{p^c_x\}_{x\in\{1,2\}} = \{p^c_1, p^c_2\}$, and the mean of the constrained agents' entrusted amount in each interval, denoted as $\{\overline{S^c_x}\}_{x\in\{1,2\}} = \{\overline{S^c_1}, \overline{S^c_2}\}$. Similarly, we inferred the frequency of the free agents' entrusted amount in intervals S_1 and S_2, respectively, denoted as $\{p^f_x\}_{x\in\{1,2\}} = \{p^f_1, p^f_2\}$, and the mean of the free agents' entrusted amount in each interval, denoted as $\{\overline{S^f_x}\}_{x\in\{1,2\}} = \{\overline{S^f_1}, \overline{S^f_2}\}$. Therefore, at time $t = 0$, agent i's entrusted amount to neighbour j followed:
(i) For $v_i = 1$, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability p^f_1 (resp. $1 - p^f_1$) and selected $\overline{S^f_1}$ (resp. $\overline{S^f_2}$) to entrust to neighbour j;
(ii) For $v_i = 0$, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability p^c_1 (resp. $1 - p^c_1$) and selected $\overline{S^c_1}$ (resp. $\overline{S^c_2}$) to entrust to the neighbour.

Strategy updating. In the strategy updating process, all agents updated their entrusted and returned amounts in each time step for all interactions. For the first stage at each time step, we assumed agents' entrusted amount S_y, $y \in \{1, 2\}$ at time $t + 1$ was in response to the entrusted amount S_x, $x \in \{1, 2\}$ received from their neighbours at time t. The combination (S_x, S_y) encompassed four response scenarios. Therefore, based on the experimental data, for constrained agents (resp. free agents), we inferred $p^c_{x,y}$ (resp. $p^f_{x,y}$) and $\overline{S^c_{x,y}}$ (resp. $\overline{S^f_{x,y}}$). At each time step for the second stage of the game, we assumed the constrained agents (resp. free agents) returned the tripled entrusted amount to neighbours at a fixed rate λ_c (resp. λ_f). As stated earlier, we also inferred the average of the returned amount ratio as λ_c (resp. λ_f) for constrained agents (resp. free agents) from the experimental data. Agent i updated their entrusted amount towards neighbour j as below.
(i) For $v_i = 1$ and $S_x = S_1$ at time t, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability $p^f_{1,1}$ (resp. $1 - p^f_{1,1}$) and selected $\overline{S^f_{1,1}}$ (resp. $\overline{S^f_{1,2}}$) to entrust to neighbour j at time $t + 1$;
(ii) For $v_i = 1$ and $S_x = S_2$ at time t, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability $p^f_{2,1}$ (resp. $1 - p^f_{2,1}$) and selected $\overline{S^f_{2,1}}$ (resp. $\overline{S^f_{2,2}}$) to entrust to neighbour j at time $t + 1$;
(iii) For $v_i = 0$ and $S_x = S_1$ at time t, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability $p^c_{1,1}$ (resp. $1 - p^c_{1,1}$) and selected $\overline{S^c_{1,1}}$ (resp. $\overline{S^c_{1,2}}$) to entrust to neighbours at time $t + 1$;
(iv) For $v_i = 0$ and $S_x = S_2$ at time t, agent i selected the entrusted amount interval S_1 (resp. S_2) with probability $p^c_{2,1}$ (resp. $1 - p^c_{2,1}$) and selected $\overline{S^c_{2,1}}$ (resp. $\overline{S^c_{2,2}}$) to entrust to neighbours at time $t + 1$.

Furthermore, agent i updated their returned amount towards neighbours as below.
(i) For $v_i = 1$, agent i returned the tripled entrusted amount to neighbours at a fixed rate λ_f.
(ii) For $v_i = 0$, agent i returned the tripled entrusted amount to neighbours at a fixed rate λ_c.

Initialization. The simulation was initialized with constrained and free agents randomly distributed on an $L \times L$ square lattice with a periodic boundary and a von Neumann neighbourhood. The fraction of free agents was denoted F, where a set of $F = 0.00 : 0.05 : 1.00$ was investigated. Each agent participated in a repeated TG against their neighbours, accruing a cumulative payoff based on the same rules as the experiment. For a comprehensive Monte Carlo simulation, we observed the averages of entrusted amount, returned amount, and payoff on the lattice of size $L = 100$ over 10^4 time steps, with the last 2×10^3 considered a stable state. All results were averaged over 1000 independent realizations for a fixed set of free agent fractions.

C.2.2 Theoretical analysis

The state of the system can be described by the frequency of agents using the entrusted amount S_x. Let $\rho_x^f(t)$ (resp. $\rho_x^c(t)$) denote the frequency of free agents (resp. constrained agents) entrusting S_x at time step t. Here, we analyse the change in $\rho_x^c(t)$ and $\rho_x^f(t)$. For constrained and free agents, there may exist $2s$ types of neighbours; that is, $\{(\ell, X)\}_{\ell\in\{1,2,\cdots,s\},X\in\{c,f\}}$, where (ℓ, X) represents an X-neighbour using the entrusted amount S_ℓ.

We begin with a focal (x, c)-agent. The probability of a configuration with k_ℓ^c (ℓ, c)-neighbours and k_ℓ^f (ℓ, f)-neighbours is

$$\mathcal{C}\left(k_\ell^c, k_\ell^f\right) = \frac{k!}{\prod_{\ell=1}^{s}\left(k_\ell^c! k_\ell^f!\right)} \prod_{\ell=1}^{s} \left((1-F)\rho_\ell^c(t)\right)^{k_\ell^c} \left(F\rho_\ell^f(t)\right)^{k_\ell^f} \tag{C6}$$

with $\sum_{\ell=1}^{c}\left(k_\ell^c + k_\ell^f\right) = k$. With such a neighbour configuration, the focal agent is expected to receive entrusted amounts

$$A\left(k_\ell^c, k_\ell^f\right) = \frac{1}{k}\sum_{\ell=1}^{s}\left(k_\ell^c S_\ell + k_\ell^f S_\ell\right) \tag{C7}$$

on average from a random neighbour.

We define $[\phi]$ to be the label of the entrusted amount in set $\mathcal{S}$ closest to value ϕ (e.g. $[S_\ell] = \ell$). The change in $\rho_x^c(t)$ is given by

$$\begin{aligned} d_t\rho_x^c(t) = &\sum_{y\neq x}\rho_y^c(t) \sum_{\sum_\ell (k_\ell^c + k_\ell^f)=k} \mathcal{C}\left(k_\ell^c, k_\ell^f\right) p^c_{[A\left(k_\ell^c, k_\ell^f\right)],x} \\ &- \rho_x^c(t) \sum_{\sum_\ell (k_\ell^c + k_\ell^f)=k} \mathcal{C}\left(k_\ell^c, k_\ell^f\right) \sum_{y\neq x} p^c_{[A\left(k_\ell^c, k_\ell^f\right)],y} \\ = &\sum_{y}\rho_y^c(t) \sum_{\sum_\ell (k_\ell^c + k_\ell^f)=k} \mathcal{C}\left(k_\ell^c, k_\ell^f\right) p^c_{[A\left(k_\ell^c, k_\ell^f\right)],x} - \rho_x^c(t). \end{aligned} \tag{C8}$$

Analogously, the change in $\rho_x^f(t)$ is given by

$$\begin{aligned} d_t\rho_x^f(t) &= \sum_{y\neq x}\rho_y^f(t)\left[\sum_{z=1}^{s}(1-F)\rho_z^c(t)p_{z,x}^f + \sum_{z=1}^{s}F\rho_z^f(t)p_{z,x}^f\right] \\ &\quad - \rho_x^f(t)\left[\sum_{z=1}^{s}(1-F)\rho_z^c(t)\sum_{y\neq x}p_{z,y}^f + \sum_{z=1}^{s}F\rho_z^f(t)\sum_{y\neq x}p_{z,y}^f\right] \\ &= \sum_{y}\rho_y^f(t)\left[\sum_{z=1}^{s}(1-F)\rho_z^c(t)p_{z,x}^f + \sum_{z=1}^{s}F\rho_z^f(t)p_{z,x}^f\right] - \rho_x^f(t). \end{aligned} \tag{C9}$$

Numerical calculation of the above two sets of equations reveals the stationary distribution of ρ_x^c and ρ_x^f. The entrusted amount of a constrained and free agent are separately

$$\begin{aligned} A^c &= k\sum_{x=1}^{s}\rho_x^c S_x, \\ A^f &= k\sum_{x=1}^{s}\rho_x^f S_x. \end{aligned} \tag{C10}$$

The entrusted amount and returned amount by an agent are separately

$$\begin{aligned} A &= (1-F)A^c + FA^f, \\ R &= 3\left[(1-F)\lambda_c + F\lambda_f\right]\left[(1-F)A^c + FA^f\right]. \end{aligned} \tag{C11}$$

The average payoff obtained by an agent is

$$Q = -A + R + (3A - R) = 2A. \tag{C12}$$

where the two terms represents the payoff derived as a trustor and as a trustee, respectively.

C.3 Ultimatum game

C.3.1 Numerical simulation

To perform the simulation based on the model outlined in the Methods section of the paper, we inferred several aspects of the agents' behaviour from the experimental data (Table **??** presents the variables overview). Specifically, in the first stage of the game, we focused on the proposed amount. To discretize the continuous strategy space, three proposal intervals, $S = \{S_1, S_2, S_3\}$, were defined based on the nature of the proposals: neutral, prosocial, and antisocial. We divided the proposals from each treatment into three equal parts. The average value of the proposals at the one-third position across all treatments was 0.6, while at the two-thirds position it was 0.8. Accordingly, the three proposal intervals were set as $S_1 \in [0, 0.6)$, $S_2 \in [0.6, 0.8)$, and $S_3 \in [0.8, 5.0]$, respectively. In the second stage, we focused on whether the agents were satisfied with the neighbours' proposals and defined the acceptance threshold of the constrained and free agents, respectively, as the basis for the agent to accept or reject the proposed amount from neighbours. We assumed that the agent's proposal and acceptance in the current round depended on their own proposal and acceptance, including the neighbours' proposal and the perceived acceptance of neighbours in the previous round. As a player cannot directly obtain the real acceptance of the neighbour in the actual interaction, we assumed the agent evaluated neighbours' acceptance based on the neighbours' response to proposals and, hence, defined the perceived acceptance threshold of the neighbours. The constrained agent evaluated the perceived acceptance of the entire neighbourhood, while the free agent evaluated the perceived acceptance of each neighbour. Constrained agents and free agents updated proposed amount and acceptance threshold following response rules $(p^c_{x_1,x_2}, p^c_{x_1,x_2,y_1,y_2;\ z_1,z_2})$ and $(p^f_{x_1,x_2}, p^f_{x_1,x_2,y_1,y_2;\ z_1,z_2})$, where $x_1, x_2, y_1, y_2, z_1, z_2 \in \{1,2,3\}$, respectively. Therefore, we inferred the exact values corresponding to $p^c_{x_1,x_2}$, $p^c_{x_1,x_2,y_1,y_2;\ z_1,z_2}$, $p^f_{x_1,x_2}$, and $p^f_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ from the experimental data.

Initial strategies. For constrained agents (resp. free agents), we counted the frequency of each combination of the proposed amount S_{x_1} and acceptance threshold $\hat{R}_{x_2}$, denoted as $p^c_{x_1,x_2}$ (resp. $p^f_{x_1,x_2}$), the mean of proposed amount, denoted as $\overline{S^c_{x_1,x_2}}$ (resp. $\overline{S^f_{x_1,x_2}}$), and the mean of the acceptance threshold, denoted as $\overline{\hat{R}^c_{x_1,x_2}}$ (resp. $\overline{\hat{R}^f_{x_1,x_2}}$) in each case. Therefore, at time $t = 0$, it followed that:
(i) For $v_i = 1$, agent i selected a combination of the proposed amount intervals and acceptance threshold intervals with probability $p^f_{x_1,x_2}$, proposed $\overline{S^f_{x_1,x_2}}$ towards their neighbour j, and assigned acceptance $\overline{\hat{R}^f_{x_1,x_2}}$;
(ii) For $v_i = 0$, agent i selected a combination of the proposed amount interval and acceptance threshold interval with probability $p^c_{x_1,x_2}$, proposed $\overline{S^c_{x_1,x_2}}$ towards their neighbours, and assigned acceptance $\overline{\hat{R}^c_{x_1,x_2}}$.

Strategy updating. In the strategy updating process, all agents updated their proposed amount and acceptance threshold in each time step for all interactions. We measured from the experimental data agents' proposed amount and acceptance threshold response $(x_1, x_2, y_1, y_2;\ z_1, z_2)$, where the combination contained 3^6 responses. Specifically, for constrained agents (resp. free agents), we counted the frequency of each response, denoted as $p^c_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ (resp. $p^f_{x_1,x_2,y_1,y_2;\ z_1,z_2}$), the corresponding average of proposed amount $S^c_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ (resp. $S^f_{x_1,x_2,y_1,y_2;\ z_1,z_2}$), and the average of acceptance threshold $R^c_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ (resp. $R^f_{x_1,x_2,y_1,y_2;\ z_1,z_2}$). Hence, it followed that:
(i) For $v_i = 1$, if agent i's interval of the proposed amount and acceptance threshold was x_1 and x_2, and neighbour j's interval of the proposed amount and perceived acceptance threshold was y_1 and y_2 at time t, then agent i' selected a response $(x_1, x_2, y_1, y_2;\ z_1, z_2)$ with probability $p^f_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ at time $t+1$, proposed $\overline{S^f}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ towards their neighbour j and assigned acceptance threshold $\overline{\hat{R}^f}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$;
(ii) For $v_i = 0$, if agent i's interval of proposed amount and acceptance threshold was x_1 and x_2, and the neighbours' interval of proposed amount and perceived acceptance threshold was y_1 and y_2 at time t, then agent i selected a response $(x_1, x_2, y_1, y_2;\ z_1, z_2)$ with probability $p^c_{x_1,x_2,y_1,y_2;\ z_1,z_2}$, proposed $\overline{S^c}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$ towards the neighbours, and assigned acceptance threshold $\overline{\hat{R}^c}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$.

Initialization. The simulation was initiated with both constrained and free agents randomly distributed on an $L \times L$ square lattice with a periodic boundary and a von Neumann neighbourhood. The fraction of free agents was denoted F, where a set of $F = 0.00 : 0.05 : 1.00$ was investigated. Each agent engaged in a repeated UG with their neighbours, accruing cumulative payoffs based on the same rules as the experiment. For a comprehensive Monte Carlo simulation, we observed the averages of the proposed amount, acceptance rate, and payoff on the lattice of size $L = 100$ over 10^4 time steps, of which the last 2×10^3 were deemed a stable state. All results were averaged over 1000 independent realizations for a fixed set of free agent fractions.

C.3.2 Theoretical analysis

The state of the system can be described by the frequency of agents using the proposed amount S_{x_1} and response S_{x_2}, denoted by $\mathbf{x} = (x_1, x_2)$. The set of all possible states is $\mathcal{X} = \{(x_1, x_2)\}_{x_1,x_2 \in \{1,2,\cdots,s\}}$. Let

$\rho^f_{(x_1,x_2)}(t)$ (resp. $\rho^c_{(x_1,x_2)}(t)$) denote the frequency of free agents (constrained agents) using the proposed amount S_{x_1} and response S_{x_2} at time step t. Here, we analyse the change in $\rho^f_{x_1,x_2}(t)$ and $\rho^c_{x_1,x_2}(t)$. For both constrained and free agents, there may exist $2s^2$ types of neighbours; that is, $\{\mathbf{x}, X)\}_{\mathbf{x}\in\mathcal{X}, X\in\{c,f\}}$, where $(\mathbf{x}, X)$ represents an X-neighbour using the proposed amount S_{x_1} and response S_{x_2}.

We begin with a focal $(\mathbf{x}, c)$-agent. The probability of a configuration with $k^c_{\mathbf{v}}$ constrained neighbours and $k^f_{\mathbf{v}}$ free neighbours is

$$\mathcal{C}\left(k^c_{\mathbf{v}}, k^f_{\mathbf{v}}\right) = \frac{k!}{\prod_{\mathbf{v}\in\mathcal{X}}\left(k^c_{\mathbf{v}}!k^f_{\mathbf{v}}!\right)} \prod_{\mathbf{v}\in\mathcal{X}} ((1-F)\rho^c_{\mathbf{v}}(t))^{k^c_{\mathbf{v}}} \left(F\rho^f_{\mathbf{v}}(t)\right)^{k^f_{\mathbf{v}}}, \tag{C13}$$

with $\sum_{\mathbf{x}\in\mathcal{X}}\left(k^c_{\mathbf{x}} + k^f_{\mathbf{x}}\right) = k$. For a constrained agent with state (x_1, x_2) and configuration $(k^c_{\mathbf{v}}, k^f_{\mathbf{v}})$, the average proposed amount from the neighbours is

$$\bar{v}_1(\mathbf{v}|\mathbf{x}) = \frac{1}{k}\sum_{\mathbf{v}\in\mathcal{X}}\left(k^c_{\mathbf{v}} S_{v_1} + k^f_{\mathbf{v}} S_{v_1}\right), \tag{C14}$$

and the perceived acceptance of neighbours is

$$\bar{v}_2(\mathbf{v}|\mathbf{x}) = S_{x_1} + \left(1 - \frac{1}{k}\sum_{\mathbf{v}\in\mathcal{X}}\left(k^c_{\mathbf{v}} + k^f_{\mathbf{v}}\right)\Theta(S_{x_1} - S_{v_2})\right)\Delta. \tag{C15}$$

We define $[\phi]$ to be the label of the allocation in set $\mathcal{S}$ closest to value ϕ (e.g. $[S_\ell] = \ell$). The change in $\rho^c_{\mathbf{x}}(t)$ is then given by

$$\begin{aligned} d_t\rho^c_{\mathbf{x}}(t) =& \sum_{\mathbf{z}\neq\mathbf{x}} \rho^c_{\mathbf{z}}(t) \sum_{\sum_{\mathbf{v}\in\mathcal{X}} k^c_{\mathbf{v}}+k^f_{\mathbf{v}}=k} \mathcal{C}\left(k^c_{\mathbf{v}}, k^f_{\mathbf{v}}\right) p^c_{z_1,z_2,[\bar{v}_1(\mathbf{v}|\mathbf{z})],[\bar{v}_2(\mathbf{v}|\mathbf{z})];\, x_1,x_2} \\ & - \rho^c_{\mathbf{x}}(t) \sum_{\sum_{\mathbf{v}\in\mathcal{X}} k^c_{\mathbf{v}}+k^f_{\mathbf{v}}=k} \mathcal{C}\left(k^c_{\mathbf{v}}, k^f_{\mathbf{v}}\right) \sum_{\mathbf{z}\neq\mathbf{x}} p^c_{x_1,x_2,[\bar{v}_1(\mathbf{v}|\mathbf{x})],[\bar{v}_2(\mathbf{v}|\mathbf{x})];\, z_1,z_2} \\ =& \sum_{\mathbf{z}} \rho^c_{\mathbf{z}}(t) \sum_{\sum_{\mathbf{v}\in\mathcal{X}} k^c_{\mathbf{v}}+k^f_{\mathbf{v}}=k} \mathcal{C}\left(k^c_{\mathbf{v}}, k^f_{\mathbf{v}}\right) p^c_{z_1,z_2,[\bar{v}_1(\mathbf{v}|\mathbf{z})],[\bar{v}_2(\mathbf{v}|\mathbf{z})];\, x_1,x_2} - \rho^c_{\mathbf{x}}(t). \end{aligned} \tag{C16}$$

Analogously, the change in $\rho^f_{\mathbf{x}}$, given by

$$\begin{aligned} d_t\rho^f_{\mathbf{x}}(t) =& \sum_{\mathbf{z}\neq\mathbf{x}} \rho^f_{\mathbf{z}}(t) \sum_{\mathbf{v}\in\mathcal{X}} \left((1-F)\rho^c_{\mathbf{v}}(t) + F\rho^f_{\mathbf{v}}(t)\right) p^f_{z_1,z_2,v_1,[z1+(1-\Theta(S_{z_1}-S_{v_2}))\Delta];\, x_1,x_2} \\ & - \rho^f_{\mathbf{x}}(t) \sum_{\mathbf{v}\in\mathcal{X}} \left((1-F)\rho^c_{\mathbf{v}}(t) + F\rho^f_{\mathbf{v}}(t)\right) \sum_{\mathbf{z}\neq\mathbf{x}} p^f_{x_1,x_2,v_1,[x_1+(1-\Theta(S_{x_1}-S_{v_2}))\Delta];\, z_1,z_2} \\ =& \sum_{\mathbf{z}} \rho^f_{\mathbf{z}}(t) \sum_{\mathbf{v}\in\mathcal{X}} \left((1-F)\rho^c_{\mathbf{v}}(t) + F\rho^f_{\mathbf{v}}(t)\right) p^f_{z_1,z_2,v_1,[z1+(1-\Theta(S_{z_1}-S_{v_2}))\Delta];\, x_1,x_2} - \rho^f_{\mathbf{x}}(t). \end{aligned} \tag{C17}$$

We then have the stationary distribution of $\rho^c_{\mathbf{x}}$ and $\rho^f_{\mathbf{x}}$. The average proposed amount (P), acceptance (R, which theoretically approximates the rejected amount), and payoff (Q) in an individual interaction are respectively

$$\begin{aligned} P &= F \sum_{\mathbf{x} \in \mathcal{X}} \rho_{\mathbf{x}}^{f} S_{x_1} + (1-F) \sum_{\mathbf{x} \in \mathcal{X}} \rho_{\mathbf{x}}^{c} S_{x_1}, \\ R &= F \sum_{\mathbf{x} \in \mathcal{X}} \rho_{\mathbf{x}}^{f} S_{x_2} + (1-F) \sum_{\mathbf{x} \in \mathcal{X}} \rho_{\mathbf{x}}^{c} S_{x_2}, \\ Q &= \frac{5}{k} \sum_{\mathbf{x}, \mathbf{y} \in \mathcal{X}} \left(F \rho_{\mathbf{x}}^{f} + (1-F) \rho_{\mathbf{x}}^{c}\right) \left(F \rho_{\mathbf{y}}^{f} + (1-F) \rho_{\mathbf{y}}^{c}\right) \Theta(S_{x_1} - S_{y_2}). \end{aligned} \tag{C18}$$

Note that we set the constrained and free agents to have the same proposal-acceptance set $\mathcal{S}$. Analogously, we can analyse the case where constrained and free players have possibly different proposal and acceptance sets. As adopted in this study, for a constrained player (resp. free player) with state $\mathbf{x}$, their proposed amount and acceptance are respectively $S_1^c(\mathbf{x})$ and $S_2^c(\mathbf{x})$ (resp. $S_1^f(\mathbf{x})$ and $S_2^f(\mathbf{x})$).

Appendix D Supplementary tables

Table D1 Basic demographic information on volunteers

Game	Treatment	Rounds	Players/Session	Sessions	Players	Women (%)	Age (SD)
Prisoner's dilemma	0% free	50	49	3	147	51	19.46 (1.22)
	25% free	50	49	3	147	54	19.30 (1.04)
	50% free	50	49	3	147	48	19.52 (1.18)
	75% free	50	49	3	147	46	19.18 (1.06)
	100% free	50	49	3	147	48	19.24 (1.10)
Trust game	0% free	50	49	3	147	63	20.01 (0.97)
	25% free	50	49	3	147	71	19.54 (1.10)
	50% free	50	49	3	147	69	19.71 (1.07)
	75% free	50	49	3	147	31	19.97 (0.94)
	100% free	50	49	3	147	65	19.44 (1.09)
Ultimatum game	0% free	50	49	3	147	41	20.03 (0.89)
	25% free	50	49	3	147	52	19.96 (0.87)
	50% free	50	49	3	147	60	19.93 (0.83)
	75% free	50	49	3	147	59	20.00 (0.88)
	100% free	50	49	3	147	59	20.24 (0.73)

Table D2 Parameters in the prisoner's dilemma game

1.1 First round strategy probabilities		
constrained	p^c	The probability that constrained agents choose cooperation
free	p^f	The probability that free agents choose cooperation
1.2 Strategy updating probabilities		
constrained	$p^c_{Ck_C}$	The probability that constrained agents choose to cooperate in the next round if constrained agents cooperating and there are k_C cooperative neighbours
	$p^c_{Dk_C}$	The probability that constrained agents choose to cooperate in the next round if constrained agents defecting and there are k_C cooperative neighbours
free	p^f_C	The probability that free agents choose to cooperate in the next round if their neighbours are cooperating
	p^f_D	The probability that free agents choose to cooperate in the next round if their neighbours are defecting

Table D3 Parameters in the trust game

2.1 Entrusted amount in the first stage of the game		
2.1.1 Entrusted amount intervals (S_1, S_2)		
2.1.2 The first round frequency of entrusted amounts in intervals S_1 and S_2		
constrained	$\{p_x^c\}_{x\in\{1,2\}}$	The frequency of constrained agents' entrusted amounts in intervals S_1 and S_2
free	$\{p_x^f\}_{x\in\{1,2\}}$	The frequency of free agents' entrusted amounts in intervals S_1 and S_2
2.1.3 The first round mean of entrusted amount in each interval		
constrained	$\{\overline{S_x^c}\}_{x\in\{1,2\}}$	The mean of constrained agents' entrusted amount in each interval
free	$\{\overline{S_x^f}\}_{x\in\{1,2\}}$	The mean of free agents' entrusted amount in each interval
2.1.4 Entrusted amount response		
	$\{(x,y)\}_{x,y\in\{1,2\}}$	The entrusted amount S_y agents choose at time $t+1$ in response to the entrusted amount S_x received from their neighbours at time t
2.1.5 Strategy updating probabilities (response rules) for the first stage of the game		
constrained	$p_{x,y}^c$	The probability that constrained agents choose the entrusted amount with interval S_y in response to the neighbours' entrusted amount with interval S_x
free	$p_{x,y}^f$	The probability that free agents choose the entrusted amount with interval S_y in response to the neighbours' entrusted amount with interval S_x
2.1.6 Strategy updating mean (response rules) for the first stage of the game		
constrained	$\overline{S_{x,y}^c}$	The mean of constrained agents' chosen entrusted amount in interval S_y in response to the neighbours' entrusted amount with interval S_x
free	$\overline{S_{x,y}^f}$	The mean of free agents' chosen entrusted amount in interval S_y in response to the neighbours' entrusted amount with interval S_x
2.2 Returned amount in the second stage of the game		
2.2.1 Fixed return ration for constrained and free agents		
constrained	λ_c	The fixed return ration of constrained agents
free	λ_f	The fixed return ration of free agents

Table D4 Parameters in the ultimatum game

3.1 Proposed amount and acceptance threshold		
3.1.1 Proposed amount intervals (S_1, S_2, S_3)		
3.1.2 The first round frequency of each combination of the proposed amount and acceptance threshold		
constrained	$p^c_{x1,x2}$	The probability that constrained agents choose proposed amount S_{x_1} and acceptance threshold S_{x_2}
free	$p^f_{x1,x2}$	The probability that free agents choose proposed amount S_{x_1} and acceptance threshold S_{x_2}
3.1.3 The first round mean of the proposed amount		
constrained	$\overline{S^c_{x_1,x_2}}$	The mean of constrained agents' proposed amount if the constrained agent chooses proposed amount S_{x_1} and acceptance threshold S_{x_2}
free	$\overline{S^f_{x_1,x_2}}$	The mean of free agents' proposed amount if the free agent chooses proposed amount S_{x_1} and acceptance threshold S_{x_2}
3.1.4 The first round mean of the acceptance threshold		
constrained	$\overline{\hat{R}^c_{x_1,x_2}}$	The mean of constrained agents' acceptance threshold if the constrained agent chooses proposed amount S_{x_1} and acceptance threshold S_{x_2}
free	$\overline{\hat{R}^f_{x_1,x_2}}$	The mean of free agents acceptance threshold if the free agent chooses proposed amount S_{x_1} and acceptance threshold S_{x_2}
3.1.5 Proposed amount and acceptance threshold response		
$\{(x1, x2, y1, y2;\ z1, z2)\}$ $x1, x2, y1, y2, z1, z2 \in \{1, 2, 3\}$		Agent's proposal $x1$ and acceptance $x2$ in the previous round, neighbours' proposal $y1$ and perceived acceptance $y2$ in the previous round, and agent's proposal $z1$ and acceptance $z2$ in the current round
3.1.6 Strategy updating frequency of each response		
constrained	$p^c_{x1,x2,y1,y2;\ z1,z2}$	The probability of each response for constrained agents
free	$p^f_{x1,x2,y1,y2;\ z1,z2}$	The probability of each response for free agents
3.1.7 Strategy updating average of the proposed amount of each response		
constrained	$\overline{S^c}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$	The average of the proposed amount of each response for constrained agents
free	$\overline{S^f}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$	The average of the proposed amount of each response for free agents
3.1.8 Strategy updating average of acceptance threshold of each response		
constrained	$\overline{\hat{R}^c}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$	The average of the acceptance threshold of each response for constrained agents
free	$\overline{\hat{R}^f}_{x_1,x_2,y_1,y_2;\ z_1,z_2}$	The average of the acceptance threshold of each response for free agents

Table D5 Cooperation frequency in the first round of mixed population treatments in the prisoner's dilemma game

Treatment	Focal constrained player					Focal free player	
	The number of free players in neighbourhood					The type of players' opponent	
	0	1	2	3	4	constrained	free
25 − 75% free	0.629	0.484	0.448	0.460	0.600	0.479	0.516
25% free	0.677	0.489	0.565	0.778	/	0.442	0.321
50% free	0.250	0.467	0.379	0.391	0.500	0.473	0.555
75% free	/	/	0.333	0.389	0.615	0.525	0.516

Table D6 Entrusted amount in the first round of mixed population treatments in the trust game

Treatment	Focal constrained player					Focal free player	
	The number of free players in neighbourhood					The type of players' opponent	
	0	1	2	3	4	constrained	free
25 − 75% free	0.683	0.704	0.728	0.698	0.717	0.996	0.999
25% free	0.685	0.681	0.670	0.735	0.500	1.021	0.900
50% free	0.667	0.745	0.785	0.744	1.060	0.909	1.117
75% free	/	/	0.750	0.639	0.612	1.083	0.956

Table D7 Proposed amount in the first round of mixed population treatments in the ultimatum game

Treatment	Focal constrained player					Focal free player	
	The number of free players in neighbourhood					The type of players' opponent	
	0	1	2	3	4	constrained	free
25 − 75% free	0.784	0.736	0.692	0.689	0.792	1.009	0.963
25% free	0.784	0.727	0.717	0.570	/	1.032	1.000
50% free	0.783	0.762	0.658	0.730	0.920	1.068	0.853
75% free	/	/	0.743	0.670	0.746	0.911	1.007

Table D8 Standard errors at treatment, individual, and session levels in the prisoner's dilemma game

Cooperation	Estimate	Std. Error	t value	p-value(adj.)	Level	Obs.
T1 vs Control	0.198	0.007	30.020	< **0.001**	Treatment	14700
T2 vs Control	0.266	0.006	41.960	< **0.001**	Treatment	14700
T3 vs Control	0.464	0.006	77.000	< **0.001**	Treatment	14700
T4 vs Control	0.662	0.005	126.060	< **0.001**	Treatment	14700
T1 vs Control	0.198	0.027	7.364	< **0.001**	Individual	14700
T2 vs Control	0.266	0.025	10.607	< **0.001**	Individual	14700
T3 vs Control	0.464	0.024	19.206	< **0.001**	Individual	14700
T4 vs Control	0.662	0.022	30.333	< **0.001**	Individual	14700
T1 vs Control	0.198	0.034	5.889	< **0.001**	Session	14700
T2 vs Control	0.266	0.029	9.075	< **0.001**	Session	14700
T3 vs Control	0.464	0.039	12.056	< **0.001**	Session	14700
T4 vs Control	0.662	0.043	15.484	< **0.001**	Session	14700

Table D9 Standard errors at treatment, individual, and session levels in the trust game

Entrusted	Estimate	Std. Error	t value	p-value(adj.)	Level	Obs.
T1 vs Control	1.111	0.024	45.560	< **0.001**	Treatment	14700
T2 vs Control	1.798	0.023	76.770	< **0.001**	Treatment	14700
T3 vs Control	2.339	0.022	107.280	< **0.001**	Treatment	14700
T4 vs Control	2.746	0.019	141.900	< **0.001**	Treatment	14700
T1 vs Control	1.111	0.122	9.117	< **0.001**	Individual	14700
T2 vs Control	1.798	0.118	15.281	< **0.001**	Individual	14700
T3 vs Control	2.339	0.101	23.248	< **0.001**	Individual	14700
T4 vs Control	2.746	0.089	31.029	< **0.001**	Individual	14700
T1 vs Control	1.111	0.530	2.095	0.145	Session	14700
T2 vs Control	1.798	0.571	3.151	**0.007**	Session	14700
T3 vs Control	2.339	0.258	9.077	< **0.001**	Session	14700
T4 vs Control	2.746	0.182	15.055	< **0.001**	Session	14700
Returned	**Estimate**	**Std. Error**	**t value**	**p-value(adj.)**	**Level**	**Obs.**
T1 vs Control	1.200	0.028	42.930	< **0.001**	Treatment	14700
T2 vs Control	2.073	0.031	65.900	< **0.001**	Treatment	14700
T3 vs Control	3.184	0.043	74.900	< **0.001**	Treatment	14700
T4 vs Control	3.869	0.041	94.160	< **0.001**	Treatment	14700
T1 vs Control	1.200	0.142	8.468	< **0.001**	Individual	14700
T2 vs Control	2.073	0.155	13.330	< **0.001**	Individual	14700
T3 vs Control	3.184	0.216	14.768	< **0.001**	Individual	14700
T4 vs Control	3.869	0.203	19.102	< **0.001**	Individual	14700
T1 vs Control	1.200	0.683	1.758	0.315	Session	14700
T2 vs Control	2.073	0.798	2.597	**0.038**	Session	14700
T3 vs Control	3.184	0.483	6.589	< **0.001**	Session	14700
T4 vs Control	3.869	0.215	17.959	< **0.001**	Session	14700

Table D10 Standard errors at treatment, individual, and session level in the ultimatum game

Proposed	Estimate	Std. Error	t value	p-value(adj.)	Level	Obs.
T1 vs Control	-0.135	0.012	-11.700	< 0.001	Treatment	14700
T2 vs Control	-0.116	0.013	-9.258	< 0.001	Treatment	14700
T3 vs Control	0.044	0.015	2.890	**0.015**	Treatment	14700
T4 vs Control	0.401	0.018	22.210	**< 0.001**	Treatment	14700
T1 vs Control	-0.135	0.049	-2.775	0.022	Individual	14700
T2 vs Control	-0.116	0.055	-2.105	0.141	Individual	14700
T3 vs Control	0.044	0.084	0.524	1.000	Individual	14700
T4 vs Control	0.401	0.104	3.848	**< 0.001**	Individual	14700
T1 vs Control	-0.135	0.148	-0.910	1.000	Session	14700
T2 vs Control	-0.116	0.064	-1.815	0.278	Session	14700
T3 vs Control	0.044	0.133	0.331	1.000	Session	14700
T4 vs Control	0.401	0.099	4.063	**< 0.001**	Session level	14700
Accepted	**Estimate**	**Std. Error**	**t value**	**p-value(adj.)**	**Cluster**	**Obs.**
T1 vs Control	-0.014	0.015	-0.967	1.000	Treatment	14700
T2 vs Control	0.036	0.016	2.296	0.087	Treatment	14700
T3 vs Control	0.240	0.018	13.640	**< 0.001**	Treatment	14700
T4 vs Control	0.639	0.020	31.960	**< 0.001**	Treatment	14700
T1 vs Control	-0.014	0.057	-0.250	1.000	Individual	14700
T2 vs Control	0.036	0.064	0.562	1.000	Individual	14700
T3 vs Control	0.240	0.091	2.653	**0.032**	Individual	14700
T4 vs Control	0.639	0.108	5.925	**< 0.001**	Individual	14700
T1 vs Control	-0.014	0.166	-0.086	1.000	Session	14700
T2 vs Control	0.036	0.114	0.315	1.000	Session	14700
T3 vs Control	0.240	0.173	1.391	0.657	Session	14700
T4 vs Control	0.639	0.123	5.209	**< 0.001**	Session	14700