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Propagation of Economic Inequality Through Reciprocity and Reputation

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Abstract

Reciprocity and reputation are powerful tools for encouraging cooperation on a broad scale. Here, we highlight a potential side effect of these social phenomena: exacerbating economic inequality. In two novel economic games, we manipulated the amount of money with which participants were endowed and then gave them the opportunity to share resources with others. We found that people reciprocated more toward higher-wealth givers, compared with lower-wealth givers, even when those givers were equally generous. Wealthier givers also achieved better reputations than less wealthy ones and therefore received more investments in a social marketplace. These discrepancies were well described by a formal model of reinforcement learning: Individuals who weighted monetary outcomes, rather than generosity, when learning about interlocutors also most strongly helped wealthier individuals. This work demonstrates that reciprocity and reputation—although globally increasing prosociality—can widen wealth gaps and provides a precise account of how inequality grows through social processes.

Keywords

social behavior, rewards, reciprocity, inequality, open data, open materials

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Folk wisdom considers virtue to be its own reward, but virtue can also pay off in cash. People who act generously often benefit in turn, both from the recipients of their help (direct reciprocity) and from others who witness or learn about their generosity (indirect reciprocity; Dal Bó, 2005; Feinberg, Willer, & Schultz, 2014; Sommerfeld, Krambeck, Semmann, & Milinski, 2007; Wedekind & Braithwaite, 2002; Wedekind & Milinski, 2000). Individuals with a reputation for generosity also enjoy increased social capital through access to new cooperative relationships, such as economic partnerships built on trust (Feinberg et al., 2014; Sylwester & Roberts, 2010).

The value of direct and indirect reciprocity is not lost on people. Individuals act more generously when they anticipate future encounters with an interlocutor or when their reputations are at stake (Barclay & Willer, 2007; Dal Bó, 2005; Milinski, Semmann, & Krambeck, 2002; Wedekind & Milinski, 2000). In fact, reciprocity and reputation are cornerstones of both evolutionary accounts of prosociality (Axelrod & Hamilton, 1981; Nowak & Sigmund, 2005; Trivers, 1971) and evidence-based policy suggestions for amplifying cooperation on a large scale (Kraft-Todd, Yoeli, Bhanot, & Rand, 2015). For instance, people are more likely to vote, donate blood, and conserve energy when their actions are observable by others (Funk, 2010; Lacetera & Macis, 2010; Yoeli, Hoffman, Rand, & Nowak, 2013).

Although reputation and reciprocity encourage cooperation, we explored a potential side effect of these social phenomena: They may benefit some individuals more than others. In studies of reciprocity, participants typically start out with an even distribution of wealth (Milinski et al., 2002; Wedekind & Milinski, 2000). By contrast, the real world features enormous and rising economic inequality (Piketty & Saez, 2014). We propose that when initial distributions of wealth are unequal, reciprocity and reputation might exacerbate economic inequality.

How might reciprocity and reputation widen wealth gaps? One possible mechanism is reward-based reinforcement learning, through which people associate actions with rewards (Gläscher, Daw, Dayan, & O'Doherty, 2010).

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Consider two "givers," one of whom starts with a $100 endowment and the other of whom starts with a $20 endowment. If each giver shares half of his or her resources, each exhibits equal levels of generosity but provides differing levels of *reward value*, or raw capital, to beneficiaries. When people experience repeated pairings of a stimulus with reward, they are more likely to return to that stimulus (Gläscher et al., 2010; Wood, 2017). Similarly, we suggest that rewards build positive affect toward another person—even when those rewards do not reflect the giver's generosity—and these positive associations can color later choices of people with whom to interact.

Indeed, recent research demonstrates that beneficiaries choose interaction partners on the basis of both generosity and reward value, in a manner well described by reinforcement-learning models (Hackel, Doll, & Amodio, 2015). That is, people choose to interact with social partners who have provided them with rewards in the past, in addition to those who have been generous. Strikingly, people continue to choose rewarding partners even in later tasks that render previous rewards irrelevant (Hackel et al., 2015). For instance, Hackel and colleagues (2015) asked participants to choose a partner for a puzzle-solving task that featured no further monetary reward. Participants strongly preferred generous givers but also had a modest preference for givers who had provided large rewards. People also display this pattern of preferences when asked to rate how much they like givers (Hackel, Mende-Siedlecki, & Amodio, 2017).

If these preferences extend to reciprocity, then wealthy people might also receive larger economic returns on equivalent acts of generosity. This preference should emerge even when people have no strategic reason to help the wealthy—for example, when people will not have any further interactions with a wealthy person. Thus, we hypothesized that people would reciprocate more with the wealthy even when doing so offers no economic benefits. This pattern would suggest that people have an intrinsic preference for helping others who have been associated with reward in the past. We tested these predictions using a series of novel economic games designed to model unequal wealth distribution and its effects on social behavior (see Fig. 1).

Study 1: Wealth-Based Reciprocity

Method

Overview. As in previous experimental manipulations of economic inequality (Nishi, Shirado, Rand, & Christakis, 2015), we endowed an initial wave of givers with either a relatively high number of points (higher-wealth givers; average = 200) or a low number of points (lower-wealth givers; average = 60). Points were converted to money at the end of the study. Givers played 36 rounds of a modified dictator game; in each round, they chose whether to share 20% or 50% of their endowment with a future participant (see Fig. 1b). Givers always chose between these two percentages. Although no givers were objectively wealthy, the manipulation of endowment size created relative inequality in the laboratory, which can indicate how wealth might affect behavior in the real world. Previous experiments have used similar manipulations to create relative inequality or alter relative social class (Nishi et al., 2015; Piff, Kraus, Côté, Cheng, & Keltner, 2010).

In a second wave of the experiment, a new set of participants ("recipients") was randomly matched with 2 higher-wealth givers and 2 lower-wealth givers and made iterated choices of which giver with whom to interact (see Fig. 1c). Each time a recipient chose a particular giver, we showed the recipient a randomly ordered choice from that giver. That is, the recipient saw the number of points the giver had available on that trial and the number of points the giver shared. Recipients actually received the points that givers chose to share on each trial. Thus, participants simultaneously learned about each giver's generosity (the average percentage of points they shared) and reward value (average number of points they shared). That is, participants learned about the average amount of money they could win by selecting a giver, above and beyond that giver's generosity. Critically, when holding generosity constant, higher-wealth givers provided more raw value than lower-wealth ones. Recipients next completed a surprise reciprocity task, in which they could share points in return with each giver. In this stage, there was no longer any advantage to interacting with wealthy givers; recipients had an equal number of points available to share with each giver. There was, therefore, no strategic reason for recipients to favor wealthy givers.

Participants. Participants were recruited through Amazon Mechanical Turk (MTurk). In Wave 1, 100 participants (50 females, 50 males; age: M = 38.84 years, range = 20–66) completed a giver role. In Wave 2, 100 participants (42 females, 58 males; age: M = 35.63 years, range = 19–65) completed a recipient role. To ensure that participants in the recipient role were meaningfully responding to the learning task (described below), we instituted an exclusion rule used in prior online studies of reinforcement learning (Gillan, Otto, Phelps, & Daw, 2015). If participants had average reaction times ±2 standard deviations from the group mean, did not respond on more than 10% of trials, or pressed the same key on more than 90% of trials, we excluded their data from analysis. We selected this rule prior to analysis during pilot testing (see the Supplemental

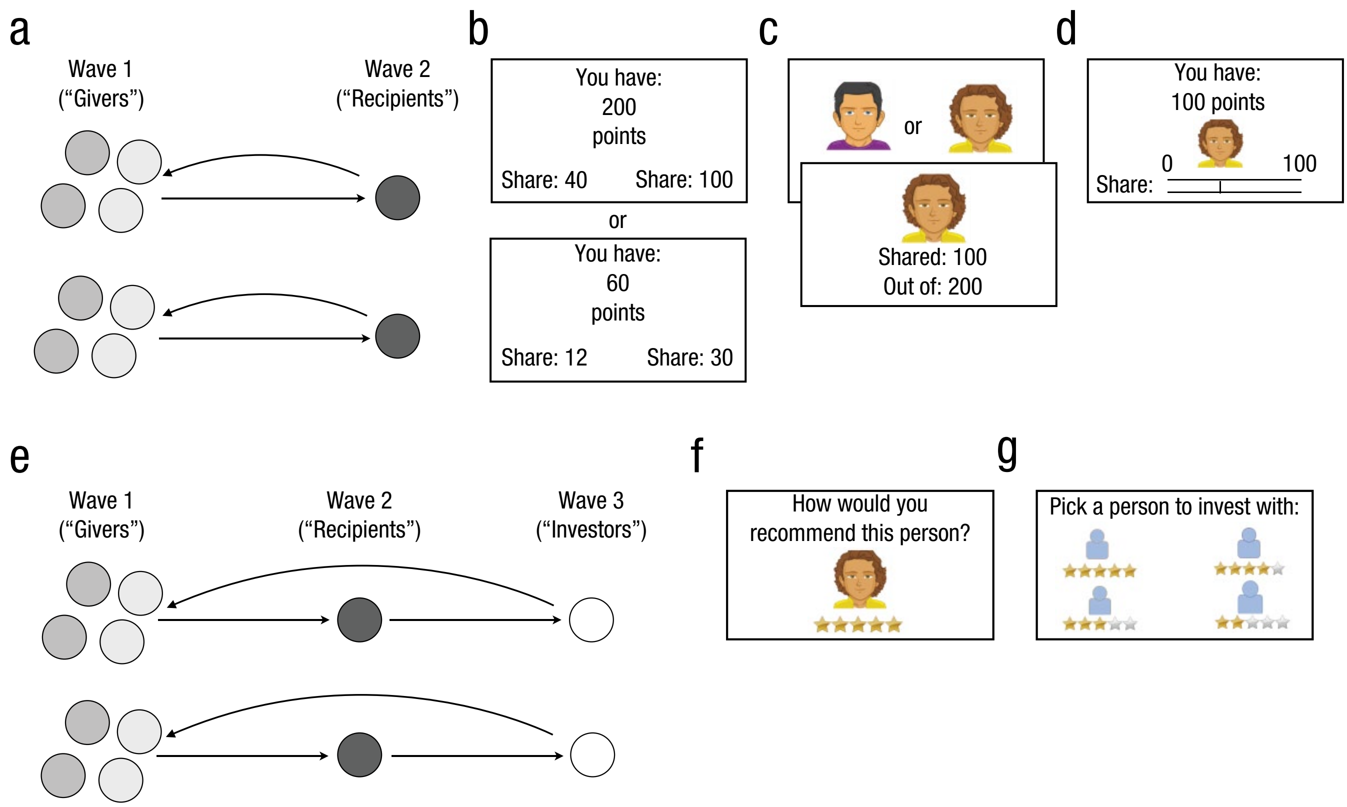

Fig. 1. Schematic of the tasks in Study 1 (a–d) and Study 2 (e–g), in which higher-wealth and lower-wealth givers earned reciprocity and reputation across waves of participants. In Study 1, participants from Wave 1 ("givers") were randomly grouped together into sets containing two higher-wealth and two lower-wealth givers (a) and matched to 1 participant from Wave 2 ("recipients"). Recipients from Wave 2 learned about and reciprocated with givers. Givers made many decisions to share either 50% or 20% from a pool of points worth money (b); each was randomly assigned a large pool of resources (higher wealth) or a small pool (lower wealth). Recipients made repeated choices to interact with 1 giver out of a pair (c). Choices were followed by feedback revealing the number of points shared by that giver, indicating the reward acquired by the recipient, as well as the pool of points that had been available to the giver, indicating the giver's generosity. In a surprise reciprocity task (d), recipients decided how much to share in return with each giver. In Study 2, each recipient from Wave 2 was further matched with a participant in Wave 3 ("investors"; e). After learning about givers, recipients in Study 2 recommended each giver for a trust game by making a one- to five-star rating (f). The third wave of participants in Study 2 completed a trust game (g), in which they chose 1 of 4 givers to trust with an investment. Each investor saw the reputation ratings provided by 1 recipient from Wave 2.

Material available online) and used it consistently across all studies. Using this rule, data from 13 participants were excluded from the analysis of Wave 2, leaving 87 participants for analysis. The sample size for Wave 2 (our primary focus of analysis) was determined on the basis of a power analysis for the smallest effect we aimed to detect—namely, a correlation between a learning parameter and wealth-based reciprocity. In a pilot study (see the Supplemental Material), this correlation (r) had a value of −.36. Assuming this effect size, we needed a sample size of 76 to achieve 90% power; we ran additional participants to maintain sufficient power after necessary participant exclusions. Informed consent was obtained from all participants. All procedures were approved by the Stanford University Research Compliance Office.

Procedure. In Wave 1, participants were informed that they would be able to repeatedly decide how to allocate a pool of points worth money between themselves and a future participant. Participants completed 36 binary allocation decisions during which a pool of points was displayed in the center of the screen, and two potential allocations were listed underneath on each side of the screen. The two options represented 50% and 20% of the point pool, respectively; the side of the screen on which each allocation appeared switched across rounds.

To manipulate inequality, we randomly assigned each giver to one of two distributions of point pools. In the higher-wealth condition (n = 51), point pools followed a Gaussian distribution with a mean of 200 and a standard deviation of 15. In the lower-wealth condition (n = 49), the point distribution had a mean of 60 and a standard deviation of 15. These means were chosen so that 20% allocations from the higher-wealth distribution and 50% allocations from the lower-wealth distribution could slightly overlap, making learning more challenging. Givers did not know that there were two possible point distributions; therefore, we did not expect giver behavior to vary on the basis of condition (for the distribution of giver allocations, see Fig. S1 in the Supplemental Material). Givers knew that a future recipient would see the amounts they share and would receive a monetary bonus accordingly. However, givers did not know that recipients would have an opportunity to reciprocate.

In Wave 2, participants (recipients) were informed that they were in a recipient role, in which they would benefit from allocations made by prior givers. Recipients first completed a learning task in which they chose to interact with givers from Wave 1; this learning task was modeled after prior work (Hackel et al., 2015). Each Wave 2 recipient was randomly matched with 2 higher-wealth and 2 lower-wealth givers from Wave 1. We did not place any other restrictions on matches. Recipients were explicitly instructed that each giver could share either 20% or 50% of a point pool. They then completed 60 trials of a learning task, in which each pair of givers appeared 10 times (in randomized order); each giver was equally likely to appear on either side of the screen. In each round, recipients saw 2 potential givers and chose 1 with whom to interact by pressing a button. Givers were represented by face avatars (created at pickaface.net) to help recipients keep track of different givers. The instructions clarified that these avatars were assigned by the experimenters. In addition, avatars were randomly assigned to different givers across participants, ensuring that any differences between face avatars (e.g., attractiveness) would not impact results.

Recipients had 2 s to make a choice on each round; this time window is consistent with past work (Hackel et al., 2015) and offers sufficient time for choices, given the iterated nature of the task. This window was limited to standardize the amount of time that each participant had available to make decisions. If participants did not make a choice within the response window, they saw a red "X" and a notice that they had not responded in time. After each choice, feedback (lasting 2 s) indicated (a) the number of points shared by the chosen giver and (b) the pool of points that had been available to that giver (e.g., "Shared: 100, Out of: 200"). From this information, the recipient could infer both the reward that the giver provided and the giver's generosity, or the percentage shared of the giver's endowment.

After completing the learning task, recipients were informed that they would have the opportunity to allocate points in return to the givers. The instructions explained that the original givers did not know that this stage would take place; this stage was, in fact, a surprise for both givers and recipients. Thus, recipients were fully aware of the choice task and instructions presented to givers, including the fact that givers did not know about the surprise reciprocity stage. Recipients made 20 allocation decisions similar to the allocations performed by the givers. For each decision, recipients saw the face avatar of 1 giver and a point pool available and indicated how much to share using a sliding bar. Each face was viewed five times, with five different point pools (20, 40, 60, 80, and 100 points). Finally, participants were debriefed and paid their base pay plus a bonus proportional to the number of points they accrued. (The average bonus in Wave 2 was 39 cents, based on a 100:1 conversion rate between points and cents. This amount is comparable with the compensation for many tasks in the MTurk marketplace; in our task, recipients received $1 as their base pay, and so the average bonus was 39% of base pay.)

Results

To analyze recipient behavior in the reciprocity phase, we fitted a mixed-effects linear regression predicting percentage shared on each trial as a function of giver wealth (higher wealth = 1, lower wealth = −1), giver generosity, and their interaction. This analysis was used given the nested structure of the data (i.e., multiple trials were embedded within participants). Generosity was defined as the percentage of trials on which givers chose the generous allocation, given that giver choices were binary. The regressor for generosity was mean-centered within participants, so that fixed-effects coefficients could be interpreted relative to each participant's mean, and z-scored between participants to allow common scaling and meaningful comparison between wealth and generosity coefficients across all participants. We allowed the predictors to interact and included fixed and random effects for all predictors. We report an estimate of R^2 for mixed-effects regression that contains two parts: marginal R^2 (R^2_{m}), which indicates the variance explained by fixed effects alone, and conditional R^2 (R^2_{c}), which indicates the variance explained by fixed and random effects together (Johnson, 2014; Nakagawa & Schielzeth, 2013). For further details, see the Supplemental Material.

Past work predicts that reciprocity would depend on givers' generosity (Wedekind & Milinski, 2000). And indeed, recipients shared a larger percentage of points with givers who frequently, as opposed to seldom, chose the generous 50% allocation, $b = 0.09$, $SE = 0.01$, $t(65.03) = 9.04$, $p < .001$, 95% confidence interval (CI) = [0.07, 0.11]. However, recipients also shared more with givers who had been assigned larger, as opposed to smaller, endowments, $b = 0.04$, $SE = 0.01$, $t(77.17) = 5.40$, $p < .001$, 95% CI = [0.02, 0.05] (total variance

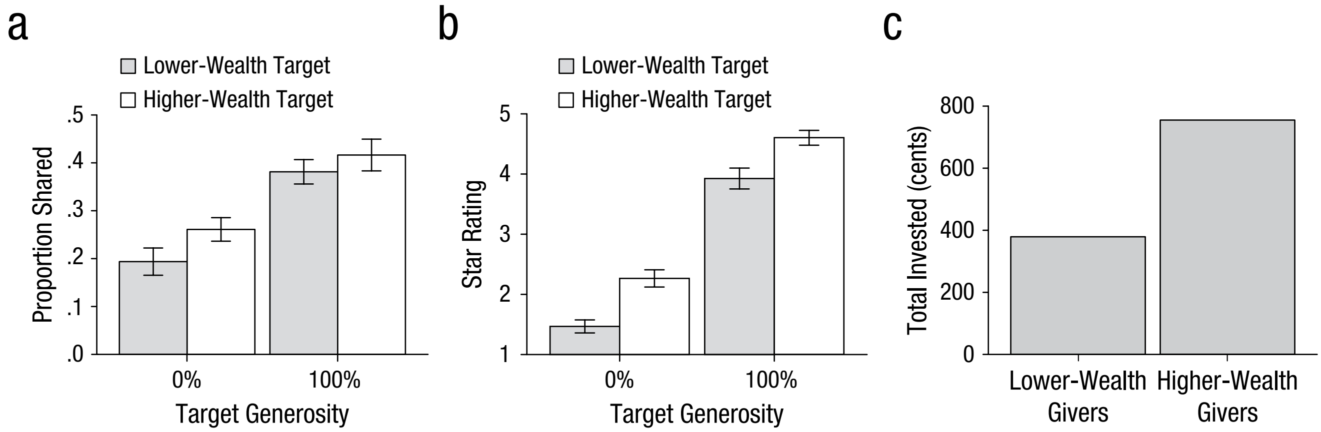

Fig. 2. Impact of wealth on reciprocity and reputation in Study 1 (a) and Study 2 (b, c). Participants shared a greater proportion of resources with higher-wealth givers (a), in addition to reciprocating more with those who were generous. This pattern held even when we considered only a subset of givers who chose a generous allocation on 0% or 100% of choices (displayed here). Participants recommended higher-wealth givers more highly than lower-wealth givers for a trust game (b), even when we considered only a subset of givers who chose a generous allocation on 0% or 100% of choices (displayed here). In panels (a) and (b), error bars represent bootstrapped standard errors of the mean (see the Supplemental Material). A small discrepancy in reputation for higher-wealth versus lower-wealth givers led a new set of participants to invest nearly twice as much money in total with higher-wealth givers (c).

explained: $R^2_m = .13$, $R^2_c = .91$; difference of coefficients for generosity vs. wealth = 0.05, $SE = 0.01$, $\chi^2(1) = 22.66$, $p < .001$, 95% CI = [0.03, 0.08]; for all coefficients, see Table S1 in the Supplemental Material). As a result, givers who began the game relatively "wealthier" also received greater social returns on equal levels of generosity.

Strikingly, this pattern held true even for givers who never chose a generous allocation (see Fig. 2a): When reciprocating toward self-serving individuals, participants shared an average of 26% of their available resources with higher-wealth givers but only 19% of their resources with lower-wealth givers. In other words, those who started off relatively wealthier gained more money through direct reciprocity, even when their actions did not warrant preferential treatment. In fact, regression estimates indicated that a lower-wealth giver would need to make 10.80 more generous allocations (out of 36 choices) than a higher-wealth giver to receive equivalent reciprocity (see the Supplemental Material). This effect replicated those found in two pilot studies ($N = 46$, $N = 141$), which also ruled out sampling bias as an explanation for these effects (see the Supplementary Material, including Tables S2–S6).

This effect was also replicated when we altered the task to reduce the salience of rewards. Our initial task made it slightly easier for participants to compute rewards (which they saw explicitly) than generosity (which they had to infer). Although it would have been quite easy for participants to infer generosity, given that they knew givers could share either 50% or 20% on each round, it remained possible that this feature of the task heightened participants' focus on reward. To rule out this possibility, we collected data from a new set of 100 participants using an inverted design in which generosity was presented explicitly and reward had to be inferred (e.g., "Shared: 50%, Out of: 200"). The results replicated those of Study 1: Participants reciprocated on the basis of generosity, $b = 0.07$, $SE = 0.01$, $t(71.49) = 6.48$, $p < .001$, 95% CI = [0.05, 0.10], and on the basis of wealth, $b = 0.03$, $SE = 0.01$, $t(84.32) = 4.60$, $p < .001$, 95% CI = [0.02, 0.05], $R^2_m = .08$, $R^2_c = .88$. This replication ruled out the possibility that our original task artificially heightened attention to rewards because of the manner in which feedback was presented (see the Supplemental Material, including Figs. S3 and S4 and Table S7).

Study 2: Wealth-Based Reputation

Method

Overview. Although higher-wealth givers, compared with lower-wealth givers, benefited more from direct reciprocity in Study 1, the effect of wealth was nonetheless dwarfed by the influence of generous character. However, wealthier individuals might benefit even more unevenly in "social marketplaces," where people select partners based on reputation. When only one person can be chosen to benefit from a cooperative relationship, reputation assumes a winner-take-all structure. This could magnify the impact of social processes on economic inequality. To test this possibility, we extended the economic game from Study 1 to model reputation in a social marketplace (see Fig. 1e).

As in Study 1, higher-wealth or lower-wealth givers made serial decisions to share generously or stingily with recipients. However, instead of directly paying back givers, recipients in Study 2 were asked to recommend each giver for a trust game (Berg, Dickhaut, & McCabe, 1995) to be played by a future participant, by assigning each giver a "Yelp-style" rating between one and five stars (see Fig. 1f). Recipients were informed that their recommendations would help a future participant choose whom to trust and could help givers by persuading new participants to invest with them. These recommendations therefore adhere to the usage of gossip for encouraging prosociality and cooperation (Feinberg et al., 2014; Sommerfeld et al., 2007). The instructions also made clear that each future participant would have exactly 20 cents available to invest; thus, there would be no strategic advantage to investing in a formerly higher-wealth giver as opposed to a lower-wealth giver. Instead, later participants would be best served by investing in trustworthy givers, presumably best reflected in their generosity, or the percentage of their endowment that these givers initially shared.

A third generation of participants ("investors") received reputational information from recipients. Each investor was matched with 1 recipient and saw that recipient's star ratings of the 4 givers with whom the recipient had interacted (see Fig. 1g). Each investor selected 1 giver (of the 4) with whom to invest and played a standard trust game (Berg et al., 1995) with the giver. In it, the investor received 20 cents that he or she could invest with 1 of the 4 givers. Any amount invested would be tripled and sent to the giver; the giver could then decide whether to pay back a fair amount, yielding a gain to both parties, or an unfair amount, yielding a loss to the investor. If reputation depends only on percentage shared, then recipients should rate generous givers highly but not favor wealthy givers. That is, they should equally judge 2 givers who always chose a generous (or stingy) allocation, even if 1 was wealthy and 1 was not.

Participants. In Wave 1, 101 participants (45 females, 56 males; age: M = 34.92 years, range = 19–70) were recruited on MTurk. In Wave 2, 100 participants (46 females, 54 males; age: M = 34.22 years, range = 18–65) were recruited on MTurk. Fifteen participants were excluded from the analysis of Wave 2 using the same exclusion criteria as in Study 1, leaving 85 participants for analysis. Sample size for Wave 2 was determined as in Study 1. Finally, 82 participants were recruited on MTurk for Wave 3 (40 females, 41 males, 1 undisclosed; age: M = 34.21 years, range = 20–66). Informed consent was obtained from all participants.

Procedure. The procedure for Wave 1 was identical to that of Study 1. Each participant was randomly assigned to the higher-wealth condition (n = 51) or the lower-wealth condition (n = 50). (For the distribution of giver allocations, see Fig. S2 in the Supplemental Material.) The procedure for Wave 2 was identical to that of Study 1, with the following exception: Instead of completing a reciprocity stage, recipients recommended each giver for a trust game. Recipients received detailed instructions explaining the rules of the trust game. Each recipient was informed that a future participant would be able to select 1 of the 4 givers he or she had learned about as a partner for the trust game and was asked to recommend each giver using a one- to five-star rating. (One participant did not respond on one rating, and 2 participants wrote in a "zero" rating one time each instead of using the one- to five-star scale provided. These three ratings were excluded from analysis, but other ratings from these 3 participants were maintained.)

In Wave 3, each participant (investor) was matched with 1 recipient from Wave 2 and saw the ratings of the 4 givers with whom the recipient had interacted. (As described above, 3 recipients from Wave 2 had one unusable rating each; therefore, these 3 participants were not carried forward to Wave 3, as it would not have been possible to show four valid ratings from these participants.) After learning the rules of the trust game, investors were asked to select 1 giver with whom to play and were next asked to indicate an amount to invest. Our aim in Wave 3 was to quantify the cost of any disparities in reputation. We expected investors to choose the highest rated givers. This stage therefore allowed us to characterize the financial ramifications of wealth-based reputation.

We required investors to invest at least two cents, for two reasons. First, this rule required them to choose carefully when selecting a partner, which they might not have done if they had planned to invest zero cents. Second, we informed participants that they would receive their full bonus only after their partner chose how much to repay, to remove any incentive to invest less and receive a bonus sooner. By requiring a minimum investment of two cents, we ensured that participants could not receive an immediate bonus by investing nothing.

Following Wave 3, we contacted givers from Wave 1 who had been selected as trust-game partners. We presented the investments made by Wave 3 investors and allowed the Wave 1 givers to respond. Winnings were paid out to participants from Waves 1 and 3 on the basis of their joint decisions. In cases in which the Wave 1 giver did not respond, we paid the Wave 3 investor according to the mean repayment observed in the rest of the sample.

Results

To analyze trust-game recommendations in Wave 2, we conducted a mixed-effects linear regression predicting star ratings on each trial as a function of giver wealth (higher wealth = 1, lower wealth = −1), giver generosity (participant-mean-centered and *z*-scored), and their interaction, as in Study 1 (for all fixed-effects regression coefficients, see Table S8 in the Supplemental Material). For further details, see the Supplemental Material.

Recipients again exhibited a bias toward higher-wealth givers, assigning them higher reputation ratings than lower-wealth givers, $b = 0.35$, $SE = 0.06$, $t(82.75) = 6.39$, $p < .001$, 95% CI = [0.24, 0.47]. Even when accounting for the larger role of generosity, $b = 1.11$, $SE = 0.05$, $t(235) = 22.42$, $p < .001$, 95% CI = [1.01, 1.21], higher-wealth givers benefited from a 0.70-star advantage, on average, relative to lower-wealth givers—total variance explained: $R^2_m = .59$, $R^2_c = .69$; linear contrast of coefficients for generosity vs. wealth: difference = 0.75, $SE = 0.08$, $\chi^2(1) = 95.10$, $p < .001$, 95% CI = [0.60, 0.91]. Thus, higher-wealth givers received a better reputation than lower-wealth givers for the trust game, even when both had proven themselves equally generous.

Again, this discrepancy persisted even when we restricted our analysis to givers who always or never made a generous allocation (see Fig. 2b). For example, higher-wealth givers who made zero generous allocations received an average rating of 2.27 stars, whereas comparable lower-wealth givers received 1.47 stars. Regression estimates indicated that a lower-wealth giver would need to make 9.36 more generous allocations (out of 36 choices) than a higher-wealth giver to receive an equal rating (see the Supplemental Material).

Reputation, in turn, intensified wealthy givers' monetary advantages over poorer ones. Investors heavily relied on recipients' star ratings when picking trustees, as expected, choosing the highest rated giver 93% of the time. (This percentage includes cases in which investors chose 1 of multiple givers who were equally highly rated.) As a result, they invested in higher-wealth givers 55 times and in lower-wealth givers only 27 times, $\chi^2(1, N = 82) = 9.56$, $p = .002$, 95% CI for the percentage of investments given to higher-wealth givers = [57, 77]. This meant that 755 cents were invested with higher-wealth givers, compared with 379 cents invested with lower-wealth givers (see Fig. 2c). In other words, the winner-take-all structure of this trust game—in which only 1 giver benefited from reputation—magnified wealth disparities, translating a reputational advantage of less than 1 point into a nearly doubled increase in investments for wealthier givers.

Studies 1 and 2: Reward-Learning Model

We next tested the prediction that reinforcement learning provides a basis for asymmetric reciprocity and reputation. We fitted recipient interaction choices as they learned about givers to a computational model validated in previous work (Hackel et al., 2015). This model characterizes learning about givers' reward value and generosity through *prediction errors*, or deviations from recipients' expectations. For instance, a giver who previously shared 20% of his or her endowment but then shared 50% would produce a generosity prediction error, acting more generously than a recipient expected. By contrast, a giver who shared 80 points in one round and 100 points in the next round would produce a reward prediction error, offering a greater reward than expected—even if he or she shared 50% on both rounds. Our model then specifies the extent to which each recipient weighs generosity and reward value when deciding with whom to interact next, through a weighting parameter (w). Thus, a recipient with a high weighting parameter learns more from the generosity of a giver, whereas a recipient with a low weighting parameter leans more on givers' reward value.

Formally, this model assumes that participants update a reward value Q and generosity estimate G following feedback on each trial t according to the following equations:

$$Q_t = Q_{t-1} + \alpha\delta_{Rt} \tag{1}$$

$$G_t = G_{t-1} + \alpha\delta_{Gt}, \tag{2}$$

where α is a free parameter representing a learning rate, δ_{Rt} represents a reward prediction error, and δ_{Gt} represents a generosity prediction error. (We fitted one learning rate to reward and generosity on the basis of prior work; Hackel et al., 2015; this feature helps reduce the number of free parameters and avoids trade-offs between learning and choice parameters, thus stabilizing the model.) Prediction errors are defined as the difference between values received and values expected for reward and generosity, as follows:

$$\delta_{Rt} = \text{reward}_t - Q_{t-1} \tag{3}$$

$$\delta_{Gt} = \text{generosity}_t - G_{t-1} \tag{4}$$

Reward was defined as the number of points shared. In prior work using this model, givers made continuous allocations, and generosity was defined as the proportion shared. In the present task, givers made binary choices, and so expected generosity (G) was defined as the probability that a giver chooses a generous allocation of 50% (generosity$_t$ = 1) over an inequitable allocation of 20% (generosity$_t$ = 0). An expected value based on generosity was therefore defined as follows:

$$GV = (G)(.50 \times P) + (1 - G)(.20 \times P), \tag{5}$$

where P is an estimate of the average number of points available, and a giver chooses the generous allocation with probability G and the inequitable allocation with probability $(1 - G)$. The estimated average point pool, P, was set to 130, which is the mean of the two true point pool distributions. Generosity was initialized to .50, representing initial uncertainty about whether or not givers would act generously, and initial reward values were initialized to 45.5 points, computed as the mean expectation given a point pool of 130 points and an equal likelihood of givers sharing 50% or 20%.

The model allowed integration of generosity-based values and reward-based values into an overall expected value (EV) according to the following equation:

$$EV = w(GV) + (1 - w)Q, \tag{6}$$

where w is a weighting parameter indicating how much participants rely on generosity values or reward values. A participant who relies only on generosity would have a weighting parameter of 1, whereas a participant who relies only on reward would have a weighting parameter of 0.

Finally, participant choices were modeled using a softmax choice function:

$$p_{i,t} = \frac{\mathrm{Exp}(\beta \times EV_{i,t})}{\sum_j \mathrm{Exp}(\beta \times EV_{j,t})}, \tag{7}$$

where β is an exploration parameter controlling stochasticity of choice, and $p_{i,t}$ is the probability of choosing option i (of j options) in trial t.

Thus, this model had three free parameters: α, w, and β (for parameter fits across studies, see Table S9 in the Supplemental Material). Parameters were estimated using maximum a posteriori estimation to optimize parameters across all choices, using priors of gamma (1.2, scale = 5) applied to exploration parameters and beta (1.1, 1.1) applied to learning rates and the weighting parameter (Hackel et al., 2015).

This model thus produced an estimate of reward-based (vs. generosity-based) learning for each participant through the weighting parameter w. We examined relative reciprocity (Study 1) or reputation (Study 2) given to higher-wealth versus lower-wealth targets as an index of wealth-based reciprocity and reputation. Specifically, we computed the average point percentage or reputation ratings given to the 2 higher-wealth givers viewed by each participant, the average given to the 2 lower-wealth givers viewed by each participant, and the difference between these values. For this difference score, a higher value indicates greater reciprocity or reputation toward higher-wealth (vs. lower-wealth) givers, and a lower value indicates the reverse. We examined the correlation between this measure and the model-derived weighting parameter.

As hypothesized, participants who learned more from rewards versus generosity subsequently shared more with higher-wealth versus lower-wealth givers (Study 1), $r(85) = -.33$, $p = .002$, 95% CI = [−.51, −.13] (see Fig. 3a), and gave higher reputation ratings to higher-wealth versus lower-wealth givers (Study 2), $r(83) = -.41$, $p < .001$, 95% CI = [−.57, −.22] (see Fig. 3b). Since the w parameter was not normally distributed, we also computed bootstrap confidence intervals as a robustness check, which yielded the same inferences in Study 1, 95% CI = [−.52, −.12], and Study 2, 95% CI = [−.57, −.24]. In other words, recipients who learned primarily from rewards gave preferential reciprocity and reputation to wealthier targets. This finding illuminates the learning process underlying wealth disparities in social marketplaces.

Discussion

Reciprocity and reputation promote cooperation and contributions to public goods (Kraft-Todd et al., 2015), but here we demonstrated that these social processes can asymmetrically benefit the wealthy. Participants reciprocated more with givers who frequently (rather than seldom) shared generous proportions of money but also reciprocated more with higher-wealth givers (rather than lower-wealth givers), who shared larger sums. Although the influence of wealth was smaller than that of generosity, participants' preference for the wealthy produced stark inequalities when only 1 giver could benefit from reputation. This is a noteworthy side effect of social economic processes, especially given dramatically rising economic inequality (Piketty & Saez, 2014). Thus, the present work raises the troubling possibility that people most reliant on social resources—because they possess few material resources of their own—may have a harder time cultivating social capital.

Our work also provides a precise learning process behind these effects. Past research suggests that social intuitions arise from prior experience (Peysakhovich & Rand, 2015; Rand et al., 2014). Here, we described a trial-by-trial learning model that predicts reciprocity. In particular, we found that wealth-based reciprocity emerges through reinforcement learning (Sutton & Barto, 1998), a well-characterized neurocognitive process in

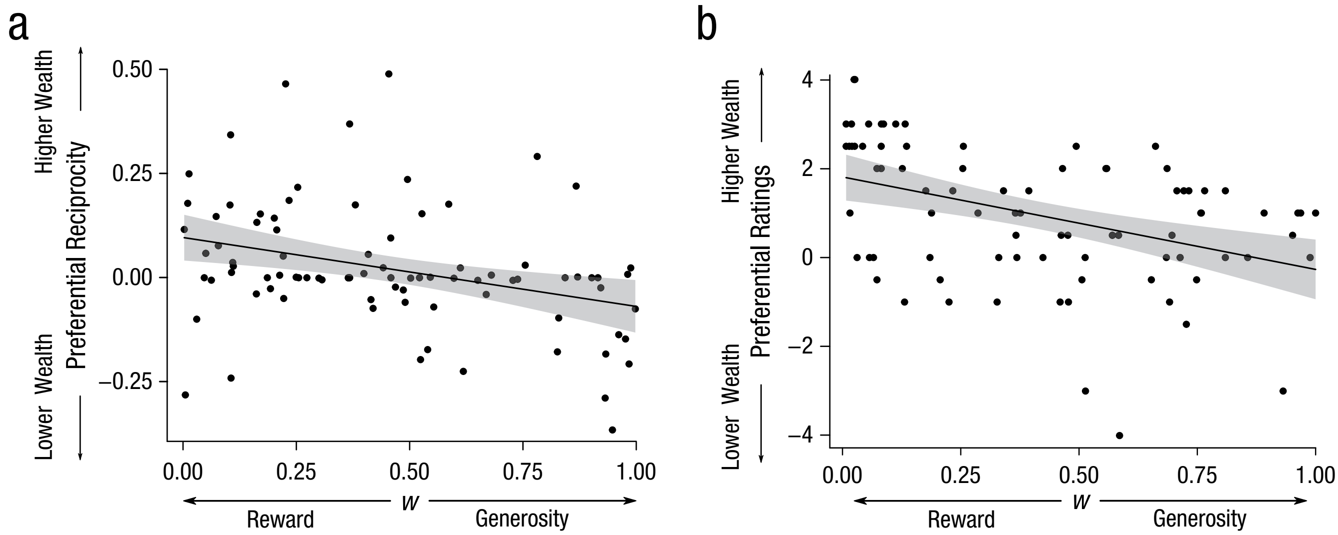

Fig. 3. Relationship between reward-based reinforcement learning and preferences for higher-wealth versus lower-wealth givers, separately for Study 1 (a) and Study 2 (b). A model-derived weighting parameter estimating reliance on reward-based versus generosity-based learning (w) correlated with (a) preferential reciprocity toward higher-wealth versus lower-wealth givers and (b) preferential reputation ratings for higher-wealth versus lower-wealth givers. Shaded regions indicate 95% confidence intervals.

which people repeat rewarded actions (Gläscher et al., 2010; Hackel et al., 2015; Thorndike, 1911). Following reinforcement learning, people like not only social partners who display generosity but also those who provide large rewards (Hackel et al., 2017). This tendency might reflect relatively habitual learning (Wood, 2017). Although people might benefit in everyday life by trading favors with the wealthy, participants gained no advantage here by privileging the wealthy, suggesting that this tendency did not rely on strategic calculation. That is, strategic self-interest might lead people to reciprocate with the wealthy when they can benefit from future trades. However, when people cannot benefit from future interactions, self-interest should not lead them to reciprocate on the basis of partners' wealth. For instance, recipients could have earned the most money in Study 1 by sharing nothing. Even under these conditions, we found that people paid a cost to reciprocate with others—suggesting an intrinsic motive to share—especially if those others had been wealthy in the prior task.

This process highlights a previously unexplored source of reciprocity. When people cannot trade favors strategically, past work suggests that people reciprocate only on the basis of others' generous actions (Wedekind & Milinski, 2000), but we found that reward learning also promotes reciprocity. Moreover, theories of other-regarding prosocial preferences hold that in the face of unequal wealth, people should privilege those with less because of a taste for equity (Fehr & Schmidt, 1999). Here, we demonstrated that reward learning leads people to increase inequity by privileging wealthier individuals. This tendency might be exacerbated when people do not know a giver's wealth and, therefore, cannot directly infer a giver's proportional generosity.

Crucially, this work also suggests boundary conditions for the social propagation of inequality and strategies through which to mitigate these effects. For instance, reward-based reinforcement learning most strongly influences people who directly gain from others, not those who merely observe those gains from a distance. Observers might more impartially assign positive reputations to generous givers, minimizing the effects of wealth.

Moreover, in our studies, individuals who learned more from generosity (vs. rewards) demonstrated more equitable reciprocity across lower-wealth and higher-wealth givers. When people are cued to focus on a given form of value, they can "tune" their attention toward relevant features of the environment (Hare, Camerer, & Rangel, 2009). This suggests that cuing people to focus on others' generosity might tune social marketplaces in a manner that mitigates their effect on wealth disparities.

Action Editor

Leaf Van Boven served as action editor for this article.

Author Contributions

L. M. Hackel and J. Zaki designed the research, L. M. Hackel collected and analyzed the data, and L. M. Hackel and J. Zaki wrote the manuscript.

Declaration of Conflicting Interests

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