The role of inequity aversion in microloan defaults

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Abstract:
Microcredit—joint liability loans to the poorest of the poor—has been touted as a powerful approach for combatting global poverty. But sustainability varies dramatically across banks. Efforts to improve the sustainability of microcredit have assumed defaults are caused by free-riding. Here, we point out that the *response* of other group members to delinquent groupmates also plays an important role in defaults. Even in the absence of any free-rider problem, some people will be unable to make their payments due to bad luck. It is other group members' unwillingness to pitch in extra – due to, among other things, not wanting to have less than other group members – that leads to default. To support this argument, we utilize the Ultimatum Game (UG), a standard paradigm from behavioral economics for measuring one's aversion to inequitable outcomes. First, we show that country-level variation in microloan default rates is strongly correlated (overall r = 0.81) with country-level UG rejection rates, but not free-riding measures. We then introduce a laboratory model "Microloan Game," and present evidence that defaults arise from inequity averse individuals refusing to make up the difference when others fail to pay their fair share. This perspective suggests a suite of new approaches for combatting defaults that leverage findings on reducing UG rejections.

Introduction

Microcredit, the offering of small uncollateralized loans, has become a popular tool for fighting poverty in recent years, particularly in the developing world. In recent years, Microfinance Institutions (MFIs) have loaned over $100 billion annually to low-income households in at least 119 countries (MIX Market 2008). These loans—largely directed at women living on less than $2 a day—are often offered to solidarity groups (Hermes & Lensink 2007). Solidarity groups are a form of joint liability, in which a group of borrowers agree to mutually insure each other's loans (Besley & Coate 1995; Armendáriz de Aghion 1999; Ghatak & Guinnane 1999). If one member of the group cannot make a payment on her loan, the other members of the solidarity group are responsible for pitching in to help her make that payment. The consequences of the group failing to bail out the delinquent member are severe: if one member defaults, the entire group is considered in default and all group members are excluded from the possibility of future loans.

The solidarity group model of microlending has been very successful in Bangladesh and other South Asian countries where it originated (Yunus 2007). However, as solidarity group lending became the modal microlending method across the world—nearly 2/3 of microcredit borrowers receive loans structured in this way (Hermes & Lensink 2007)—it became clear that the success of solidarity groups in South Asia was due to more than just the lending model.

Of course, which outcomes ought to be emphasized as indexing success—e.g., poverty reduction, savings, well-being broadly construed, women's empowerment, education, etc. (Karlan & Zinman 2011; Banerjee, Duflo, et al. 2015)—and how to measure those outcomes, are topics of debate (Awaworyi Churchill & Nuhu 2016; Odell 2010). Further, evidence that microloans have a positive impact on such local outcomes is quite mixed, both within and between studies (Pitt & Khandker 1998; Khandker 2005; Morduch & Haley 2002; Banerjee, Duflo, et al. 2015; Banerjee, Karlan, et al. 2015; Karlan & Zinman 2009; Chemin 2008; Duvendack & Palmer-Jones 2012; Attanasio et al. 2015). Looking beyond local impact, others have examined the effects of microlending on macroeconomic outcomes, like inequality, and found favorable effects (Hisako & Shigeyuki 2009). One outcome MFIs and policy makers attend to is default rates, because achieving sufficiently low default rates is important for financial sustainability. Here, we will examine the psychology that underlies microloan default and the high variation in default rates across countries that has been observed. An understanding of such variation in default rates, and their underlying psychology, could aid MFIs and policy makers as they decide how to structure loans (e.g., joint versus individual liability loans) across borrower pools.

There is significant country-level variation, $F(118, 11601) = 12.15$, $p < 0.001$, and region-level variation, $F(5, 11601) = 63.11$, $p < 0.001$, in default rates (see Figure 1 below), with banks in many countries facing default rates high enough to keep microlending from being self-sustaining (i.e. functioning without reliance on charitable donations; Hermes & Lensink 2011).

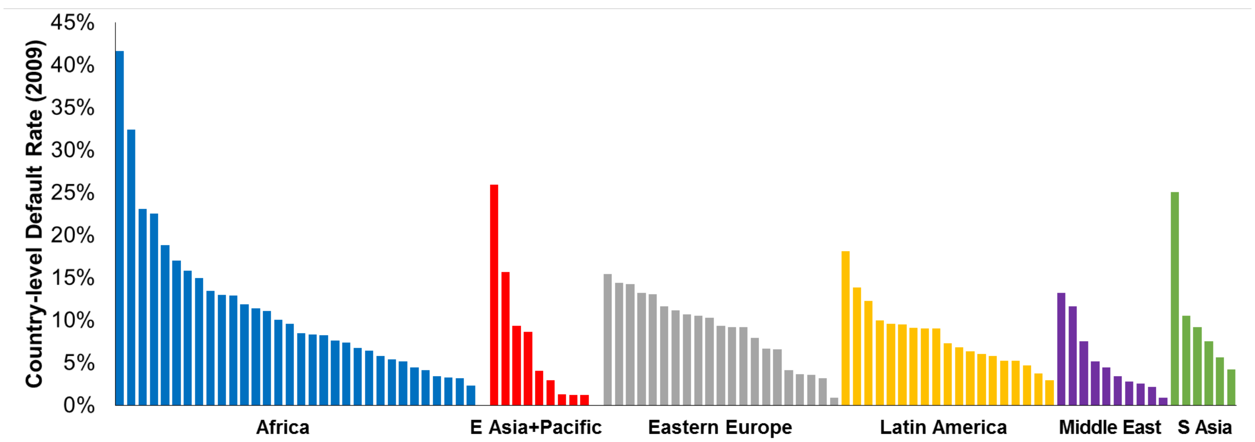

Figure 1. *There is clear variation across countries in microloan default rates, and default rates can be extremely high. Each bar represents the mean default rates of banks in a given country during 2009, which range from 0% to over 40%. Countries are grouped into five regions, represented by different colored bars (Middle East includes North Africa).*

Repayment theories

What causes defaults, and how can lenders and policy makers reduce defaults where they are prevalent? Most research on microcredit has tried to explain why individuals make any contributions to repay the microloan at all—since loans to solidarity groups are both uncollateralized and susceptible to free-riding, why do individuals not shirk on their payments, leading to high default rates across the board (Stiglitz 1990; Besley & Coate 1995; Armendáriz de Aghion 1999; Armendáriz de Aghion & Morduch 2000; Morduch 1999; Wydick 2001; Field & Pande 2008)?

One set of answers propose that the collateralization and free-rider problems can both be addressed by collateralizing the social capital that exists within and outside borrower groups. For example, borrowers who would face external sanctions in the event of a default are incentivized to repay their microloans (Besley & Coate 1995), as are those who face within group peer pressure and sanctioning (Paxton, Graham, & Thraen 2000). Others, however, have emphasized the role of harmonious social relationships, both internal and external to borrower groups, in fostering (rather than coercing) repayment (Griffin & Husted 2015). Another set of repayment theories suggest that peer monitoring and screening (e.g., requiring character references for prospective borrowers) can allow solidarity groups to exclude unreliable borrowers who take on too much risk (Stiglitz 1990) or who are characteristically unlikely to repay their loans (Armendáriz de Aghion & Morduch 2005), and thus achieve better outcomes (Banerjee et al. 1994). Similarly, borrowers may learn useful business strategies from peers who are already successful through mentorship programs, thereby reducing defaults that may be caused by inexperienced entrepreneurs who learn by trial and error (Barboza & Barreto 2006).

Inequity aversion in microloans

Many of the repayment theories described above provide compelling solutions to the free-rider problem: both social capital and peer monitoring create incentives to cooperate, as does the "shadow of the future" (Bó 2005) cast by the basic repeated interaction structure of microloans and the possibility of peer punishment (Czura 2015).

Here, we propose that there is another factor that can drive default rates, even in contexts where the free-rider problem has been resolved by social capital, peer monitoring, and repeated game effects: how people respond when *others* are unable to make their payments. That is, what determines if people are willing or unwilling to pitch in extra when someone else in their solidarity group cannot afford to pay his or her full installment? Given that borrowers are typically living under conditions of extreme poverty, they are highly susceptible to income shocks (Morduch 1994). Thus, even in the absence of free-riding, people will sometimes fail to make their full payments just due to chance and misfortune, and it is essential for a solidary group's survival that others are willing to chip in to cover these shortfalls.

Put differently, in solidarity group lending, groups don't simply default because a group member can't make her payment; groups default when the rest of the group cannot, or will not, bail out those members who are unable to make their full payments. From this perspective, an important question is therefore: what makes a borrower refuse to pay a small cost to bail out another group member, even when doing so causes her to incur the much larger cost of foregoing all future loans?

Here, we shed light on microfinance defaults by leveraging the fact that this question, in a slightly different form, has received a great deal of attention in the behavioral economics literature using the Ultimatum Game (UG). In the UG, a "proposer" makes an offer of how to split a sum of money with a "responder". The responder can either accept, or reject in which case neither player receives anything. When a responder rejects a low (but non-zero) offer, she is forgoing the offered amount in order to reduce the proposer's payoff. Although this behavior is inconsistent with rational self-interest, a large body of empirical evidence shows that many people do indeed reject low offers in 1-shot anonymous UGs (Camerer 2003), even when the stakes are quite high (e.g. 1 month's salary; Andersen et al. 2011). This evidence suggests that people derive disutility from receiving less than a normative "fair share" from an exchange (i.e. show "disadvantageous inequity aversion" (Fehr & Schmidt 1999)), and thus are willing to pay costs to obtain a result that is considered more fair – even when doing so reduces everyone's earnings.

Our key argument is that inequity aversion – the same psychology that causes UG rejections – leads borrowers to refuse to bail out delinquent members of their solidarity group, despite the long-run individual costs of allowing the group to default. To see why, consider the differences between a money-maximizing and an inequity averse decision-maker in a stylized conceptual model of the microloan interaction among the members of a solidarity group.

We consider a stochastically repeated game. In each period of the microloan interaction, each member of the solidarity group receives an endowment, and decides how much to contribute to the group's repayment effort. The group must reach a total level of contribution of at least T in order to avoid default. If the group defaults, all members are excluded from any future loans, and thus earn payoff 0 in all subsequent periods. If the group does not default, they can continue on in the next period, and each group member i earns expected payoff b_i, which is a function of the continuation probability (i.e. the likelihood that the group does not disband for reasons other than default), the income distribution across the group members, the default threshold T, and the strategies of the other group members. Our argument will hold regardless of the functional form of b. We will assume that if a group member fails to make the full payment on her loan, falling short by C units, the game enters the "pitching in" stage. In this stage, each of the non-delinquent group members in turn are given the opportunity to pitch in C units to make the group compliant. If the first non-delinquent group member pitches in enough that the threshold is met, the game continues to the next period. If not, the choice passes to the next non-delinquent member. If the non-delinquent group members fail to pitch in enough, the group defaults.

A player's strategy in this game therefore constitutes their choice of how much to contribute in the contribution stage, and whether to pitch in the required units in the pitching in stage. Given that the game is repeated, conditional strategies are possible in which choices in each stage depend on the outcome of previous rounds. For simplicity, however, we focus on a single decision (unconditional strategy) in the pitching in stage, facing the final non-delinquent group member in the case where all other non-delinquent group members have elected not to pitch in. A money maximizing player will pitch in C as long as $b_i > C$; that is, if the individual benefits to that player of the group persisting are greater than the cost of pitching in.

Those who show disadvantageous inequity aversion, however, incur a psychological cost when others earn more than them – and pitching in necessarily causes one to earn less than the other non-delinquent group members who do not pitch in, as well as the delinquent player in the case that delinquency is due to free-riding rather than an inability to contribute[1]. Let α_i be the inequity-aversion-related disutility that pitching in C units causes for group member i. Thus, an inequity averse group member will contribute if $b_i > C + \alpha_i$ holds. As a result, the more inequity averse a player is, the larger the expected monetary benefit from the group avoiding default must be in order for her to prefer pitching in to letting the group fail. Thus, just as inequity averse decision-makers are less likely to accept unfair offers in the UG than money-maximizers, inequity averse decision-makers are also less likely to pitch in when their microloan group falls short of its repayment threshold, leading to greater likelihood of default in groups of inequity averse players.

In this paper, we provide empirical and experimental support for this proposed connection between inequity aversion as indicated by UG rejections and microloan default. In doing so, we aim to shed new light on why solidarity group microloans fail, what explains cross-country variation in such failures, and what approaches might be employed to reduce such failures.

Empirical data

Methods

To provide initial empirical support for the argument that inequity aversion plays a role in determining solidarity group success, and in explaining cross-country variation in default rates, we used several publicly available data sources to compile our dataset for the microcredit outcomes analyses. These sources include the Microfinance Information Exchange (MIX) (MIX Market 2008), the World Values Survey trust index (World Values Survey Association 2009), the Global Barometer Survey (Global Barometer 2009), economic games data from dozens of countries compiled in two meta-analyses one for Ultimatum Game (UG) (Oosterbeek et al. 2004) and one for Trust Game (TG) (Johnson & Mislin 2008), and the World Bank database for GDP, GDP per capita, GDP growth, Gini index and poverty data (World Bank Group 2012). For any

[1] We note that how borrowers form beliefs about whether others are free-riding is relevant to the decision-making process, but it is beyond the scope of this model.

given analysis, we included all countries for which we had microfinance outcomes during the relevant time span and the corresponding predictor variables.

All the data regarding the performance and makeup of MFIs were obtained through the MIX (MIX Market 2008). The MIX is an online database founded in 2002, which makes available a variety of data from thousands of MFIs in most of the world's developing nations. Through the MIX, we procured rates of at-risk portfolios, loan portfolio yields, percentage of women borrowers and a number of other indicators relevant to these and other analyses. Most notably, the percentage of women borrowers is of interest as a predicting variable based on fieldwork done by D'Espallier and colleagues (D'espallier et al. 2011), which showed that homogeneity of group gender composition predicted lower default rates[2].

Because MFIs have varying accounting practices when dealing with unpaid loans, the MIX reports the value of loans that are at risk, meaning having at least one installment past due for more than 30 days[3]. This includes the value of unpaid principle, both past and future, but not accrued interest, and is standardized by dividing the at-risk loan value by the MFI's gross portfolio value. This is the standard proxy used for default rates in microlending. The 'real yield on gross portfolio' indicator is the ratio of interest and fees on the loan portfolio to the average gross loan portfolio, controlling for inflation, and so acts as a proxy for interest rates. The percentage of borrowers who are female is calculated by dividing the number of female borrowers by the total number of borrowers.

Over the last 30 years, there have been six waves of World Values Survey collected in almost 100 countries. The full survey captures many attitudes, but our primary interest were those pertaining to trustworthiness and civic cooperation. The trust question of interest is: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?". Participants then choose between "Most people can be trusted" and "You

[2] Although none of the MFIs in our sample had less than 50% female borrowers, making it impossible to determine the effect of having male dominated groups, we do find a relationship between the percentage of borrowers who are female and default rates that is consistent with D'Espallier et al.

[3] Here we use portfolios at risk at 30 days because this is the most commonly reported measure in the MIX, and therefore has the most reliable and robust data. Unfortunately, complete default data is not available.

can never be too careful when dealing with others”. The Trust Index is calculated as: Trust Index = 100 + (% Most people can be trusted) - (% Can´t be too careful). For the regressions presented in Table S3, we augmented the World Values Survey trust index data with data from the Global Barometer Survey, which asks, among other questions, the exact trust index question asked by the World Values Survey. We added trust index values from a few countries for which we had UG and MIX data, but no World Values Survey trust index data in order to keep our sample at the maximum possible size. Beyond the trust index, we also used three questions from the World Values Survey to determine what other researchers (Herrmann et al. 2008) have called ‘civic cooperation’. Civic cooperation measure attitudes towards tax evasion, abuse of social welfare programs, and dodging fares on public transportation (literal free-riding). This composite has been shown to be strongly predictive of cooperation (anti-free-riding) behavior (Herrmann et al. 2008).

Although surveys yield important information about how people expect themselves and others to behave, they do not always reveal strategies in the way economic games do. In order to distinguish between attitudinal and behavioral trust, trustworthiness, and tendency to punish, we use cross-cultural economic games data. UG and TG data were taken from the meta-analyses mentioned above that were designed to be sensitive to cross-cultural differences in the playing of these games, and so the criteria for inclusion between the meta-analyses were similar.

We also pulled democracy ranking and corruption ranking data from the World Audit (World Audit 2016) as well as rule of law data from the World Justice Project (Agrast 2013). Lastly, Gini index, GDP per capita, GDP and GDP growth were gathered from the World Bank database which collects a number of developmental indicators dating from 1960.

We restrict our analyses to 2007 and after, because prior to that year there is little data on which loan structures are most prevalent. The MIX does not collect data on loan structure, but an empirical survey from 2007 (Hermes & Lensink 2007) found that approximately 2/3 of borrowers at that time received solidarity group loans. So, for that reason, we have restricted our analyses to after 2007 in order to be sure that we are looking at microlending outcomes that reflect the relevant loan structure of solidarity groups.

Results

We find that the UG rejection rate in a given country is strongly correlated with that country's microloan default rate (r = 0.81, $p < 0.001$; Figure 2; averaging default rates across the period 2007-2014). This relationship held for all but one of the individual years in that eight-year range, and was robust to (i) controlling for UG offers (to partially address the fact that we are analyzing overall rejection rates and not minimum acceptable offers); (ii) controlling for a set of economic development indicators including GDP, GDP growth, GDP per capita, and Gini; (iii) analyzing the data at the bank level rather than the country level data; and (iv) excluding Papua New Guinea (an extreme value). See supplement for details and further analyses using additional indicators mentioned above.

Conversely, we found no evidence that defaults were negatively related to prosociality (i.e. associated with free-riding), using various different measures (Peysakhovich et al. 2014). First, we combined default rate data with a different cross-cultural dataset of Trust Game play in 18 countries (Johnson & Mislin 2008), and found a non-robust association in the *opposite* direction, with default rates being (if anything) *positively* correlated with trust, r = 0.559, $p = 0.016$, and trustworthiness, r = 0.392, $p = 0.107$, but these relationships failed to reach conventional significance levels when including economic controls, $p > 0.05$ for both. Second, we combined default rate data with the World Values Survey (56 countries in both World Values Survey and default rate dataset), and found no correlation between default rates and trust, r = -0.154, $p = 0.245$, or strength of civic norms of cooperation, r = 0.056, $p = 0.682$, both of which are often used as proxies for prosociality (Herrmann et al. 2008; Peysakhovich et al. 2014). See supplement for additional analyses.

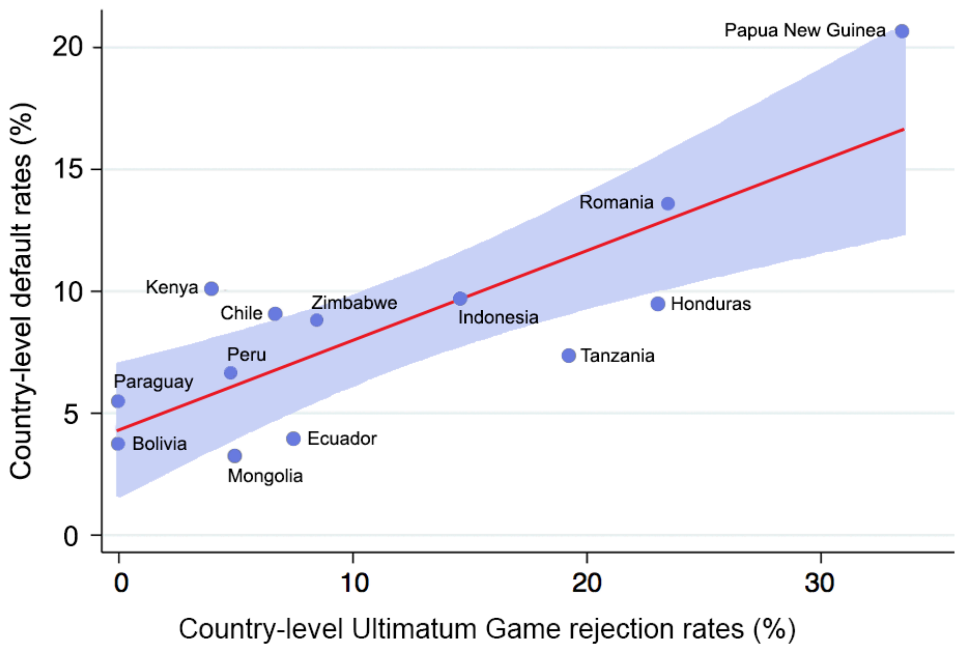

Figure 2. *Microloan default rates are strongly correlated with Ultimatum Game rejection rates across countries. Shown are country-level default rates averaged across an 8-year span (2007-2014). UG rejection rates are highly correlated with default rates,* $r = 0.812$, $p < 0.001$, $R^2 = 66\%$. *95% confidence intervals are shown for the regression line.*

The fact that UG rejections predict cross-cultural variation in microcredit default rates, while prosociality does not, supports our emphasis on borrowers' *responses* to others' behavior above any beyond borrowers' *own* inclination towards cooperation versus free-riding. Of course, these kinds of cross-sectional analyses must be taken with a grain of salt because they suffer from all the typical limitations inherent in correlational analyses and borrower populations may differ from the populations surveyed on relevant dimensions. However, we do take these results as suggestive of a mechanism—inequity aversion—that is not typically discussed in the microlending context (but see Griffin & Husted 2015 for some hints of this).

Experimental Data

Methods

To provide further evidence for this interpretation of microloan defaults, we complement this field data with an individual-level, online laboratory experiment. In this experiment, we place participants into groups and examine the relationship between Ultimatum Game Minimum Acceptable Offers (UG MAOs; the lowest offer someone would be willing to accept) within the group, and the group's behavior in a novel economic game, the Microloan Game, that we developed. In the game theoretic tradition, the Microloan Game is an abstraction that, while it omits many elements of real-world solidarity group-based microcredit, aims to capture the key strategic features of such interactions: that (i) players are engaged in a repeated, potentially lucrative group endeavor that requires regular financial investment (i.e. loan repayment) to continue; (ii) that some group members are either unable or unwilling to make that investment in any given period, leading to shortfalls; and (iii) that when such shortfalls occur, other group members can pitch in more money to make up the shortfall.

Specifically, in the Microloan Game, participants played a repeated game in groups of three. Each round of the Microloan Game consisted of two stages. (Although we herein describe the game in terms related to microcredit loan payments, the game was presented to participants in neutral language without any mention of loans, debt, or repayment.)

Upon entering the study, participants were randomly assigned to a group, and each group was randomly assigned to a condition. In Stage 1, each of the three group members was given a random initial endowment representing their income in a given loan period (between 20 and 500 monetary units, MUs, with an average of 340 MUs; the random endowment allocation procedure is described in more detail below). Each group member then decided how much of that endowment to keep for themselves versus contribute to the group, representing their decision regarding repayment of their microloan debt. Participants were informed that each of the three group members was required to contribute 200 MUs per round in order to avoid group default. If fewer than 600 MUs in total (200 MUs per member) were contributed, the contribution threshold was not met and the game entered Stage 2.

In Stage 2, all players were told the number of additional MUs required to meet the contribution threshold, and they were given the opportunity (in random order) to "pitch in" more units if they chose to do so. Participants could not waste MUs by over-contributing, and were aware of this fact because pitching in was done sequentially and the remaining balance due was displayed, and participants could not use earnings from past rounds to cover the shortfall of the current round.

If the 600 MU goal was not reached by the end of Stage 2, the game ended and no further earnings were possible (i.e. the group defaulted on their loan). If at least 600 MUs were contributed (either directly in Stage 1, or by the end of Stage 2), the game had the chance to continue on for another round (in the absence of default, the game lasted 8 rounds for certain, and then transitioned to a stochastically repeated game with 50% continuation probability; as per a randomization scheme presented in (Bó & Fréchette 2011)). The order in which participants pitched in was randomized and participants were not informed of the order in which group members were given the opportunity to pitch in (although they did always know the outstanding amount needed to reach the continuation threshold), and thus the only way of given player could be certain that the group would avoid default would be to pitch in the full amount required themselves. As a result, players had some personal incentive to make sure the group met its 600 MU contribution goal, in order to be able to earn more units in future rounds[4]; but also had the opportunity to free-ride by contributing less than 200 MUs with the hope that others would make up the difference. Critically, however, participants did not know whether lack of contribution by other players was due to the inability to contribute (because of a small endowment), or just due to free-riding.

Solidarity groups are often faced with the situation in which one or more members are unable to pay, as income for the typical participant is highly variable (Dercon 2002; Morduch 1994). To incorporate this into our lab Microloan Game, we forced incomes to differ between players and across rounds of the game: while each participant received an average of 340 MUs each round, each received a different randomly-sampled amount. In particular, the sampling was designed such that one player each round received fewer than 200 MUs, and thus was unable to repay their share of the 600 MU contribution goal. Players were informed only that in each round they

[4] The Microloan Game has a similar strategic structure to a multiplayer snowdrift/anti-coordination game, or step-level public goods game (Croson & Marks 2000). These games include equilibria with non-zero contribution levels, and it is in this sense that we mean that a personal incentive may exist for money-maximizers to contribute.

would receive a randomly determined endowment of between 0 and 500 MUs, and were given no information about the endowments of the other players or the manner in which endowments were generated (modeling the real-world ambiguity regarding others' incomes). Thus, even in the absence of any free-riding, avoiding default in the Microloan Game depended on (at least) one of the two higher-endowment players contributing more than 200 MUs each round, despite not knowing how many MUs the other participants received – and thus having uncertainty about whether others' non-contribution was driven by free-riding or bad luck. In keeping with common practice in experimental economics, and in order to have a unidimensional focus on inequity, we shuffled participant IDs between each round. That is, because we shuffled participant IDs between each round, we allowed participants to act on a motivation to avoid disadvantageous inequity without introducing complexities that arise from the presence of reputation. Of course, this reduces the ecological validity of the game, but makes it more straightforward to make inferences about the role of disadvantageous inequity aversion in microlending. See supplement for experimental instructions.

We hypothesized that, as with real-world solidarity groups, there would be substantial variance in default rates across our experimental groups in the Microloan Game, and that the psychology of inequity aversion would play a major role in explaining this variation. To test this hypothesis, we had participants play a UG prior to the beginning of the Microloan Game. In the UG, participants made decisions in both roles (specifying an offer as Player 1, and a minimal acceptable offer, MAO, below which they would reject as Player 2). Players did not receive feedback on the UG's outcome until the experiment was complete to prevent contamination effects; half of participants were assigned to be Player 1, the other half Player 2, and payment was determined on random pairings after the fact.

We predicted that a group's likelihood of defaulting in the Microloan Game would be determined by the UG MAOs of its members. In particular, because the group's shortfall could typically be made up (and default avoided) by just one group member chipping in the extra amount, what matters for preventing defaults is the least inequity averse group member – or, put differently, the failure of a group in the Microloan Game should be predicted by the lowest MAO among its members. The higher the lowest MAO in a group is, the less likely someone will be willing to chip in, and the less likely the group will be to succeed (predicting a positive relationship between Microloan Game default and minimum MAO in the group).

Recall that above, when we compared how money-maximizing and inequity averse decision-makers treat the solidarity group interaction, we showed that money-maximizers ought to be more likely to both accept low offers in the UG (i.e., have low MAOs) and more likely to pitch in to meet a threshold in a game like the Microloan Game than inequity averse decision-makers. This allows us to predict Microloan Game outcomes at the group level using individual level preferences elicited using the UG.

Finally, we assessed the robustness of this prediction regarding the importance of inequity aversion for Microloan Game default with a second experimental condition designed to accomplish two goals. First, we wanted to "stack the deck" in favor of the importance of free-riding by emphasizing the social dilemma dimension of the Microloan Game. Second, we wanted to show that, because inequity averse decision-makers *already* view the Microloan Game as a social dilemma (and money-maximizers are already prepared to pitch in when the value of the game continuing is greater than the cost of pitching in), framing the game as a social dilemma should not affect the relationship between inequity aversion and game play. In this "Social Dilemma" condition, the game was expressly framed as a *collective* goods problem: players were told that the *group as a whole* was required to contribute 600 MUs per round (and the group could, one member at a time, pitch in to cover short-falls), in contrast to the baseline condition where players were told they were *individually* responsible for contributing 200 MUs each (and could individually pitch in).

To test these predictions, we recruited 360 U.S. participants from Amazon's Mechanical Turk (M_{age} = 34.99, 71% female; Mechanical Turk offers a subject pool that is much more diverse than just college undergraduates; Horton et al. 2011) to play the UG and the Microloan Game. In line with standard MTurk wages, participants were paid a show-up fee plus a bonus based on their earnings in the game, using an exchange rate of 10 MUs per cent. A randomization check indicated that UG MAOs did not differ significantly between participants randomized into the Baseline versus Social Dilemma condition in the Microloan game (Ranksum, z = 1.303, p =

.193). The mean UG MAO was 67 MUs, and the distribution had modes at 100 and 50, and 20% of MAOs were at or below 40.

All analyses are conducted at the level of the 3-player Microloan Game group, with one observation per group. We consider three different measures of a group's (lack of) success: whether the group defaulted at any point in the game, whether the group defaulted in the very first round, and the fraction of total rounds in which the group was in default which was determined by dividing the number of completed rounds by the number of possible rounds determined by the stopping algorithm described above. We then predict these measures using the level of inequity aversion of the least inequity averse group member (i.e. the lowest UG MAO of the three group members): as described above, because it only takes one person to pitch in to the save the group from default, what matters is the unwillingness of the least unwilling group member. For the binary Microloan Game failure measures, we use logistic regression, and for the continuous failure measure we use OLS regression with robust standard errors; all coefficients for continuous variables are standardized.

Results

As expected, we observed a positive relationship between a group's failure in the Microloan Game and the group's minimum UG MAO (whether the group defaulted at any point in the game, $\beta = 0.64$, SE = 0.24, $p = 0.008$; whether the group defaulted in the very first round, $\beta = 0.61$, SE = 0.22, $p = 0.006$; fraction of total rounds in which the group was in default, $\beta = 0.09$, SE = 0.04, $p = 0.028$). See Table 1 and Figure 3. This suggests that a group defaults when the least inequity averse group member's willingness to incur costly punishment is sufficiently high – that is, when no group members are willing to pitch in because they are all too inequity averse. We also observed a significant effect of the Social Dilemma frame on Microloan Game group failure (whether the group defaulted at any point, $\beta = 1.59$, SE = 0.48, $p < 0.001$, whether the group defaulted in the first round, $\beta = 1.31$, SE = 0.44, $p = 0.003$; fraction of total rounds in which the group was in default, $\beta = 0.28$, SE = 0.07, $p < 0.001$). This serves as a manipulation check confirming that our Social Dilemma frame successfully induced greater free-riding. Critically, however, there was no significant interaction between minimum UG MAO and condition (whether the group defaulted at any point, β = 0.03, SE = 0.54, p = 0.951; whether the group defaulted in the very first round, β = 0.06, SE = 0.45, p = 0.888; fraction of total rounds in which the group was not in default, β = 0.04, SE = 0.08, p = 0.639). This shows that the MAO relationship was robust to emphasizing the social dilemma component of the Microloan Game.

Table 1. *Regression results from the experimental data. Participants were more likely to default at some point (specifications 1 and 2) and in the first round (specifications 3 and 4) if their group minimum MAO was higher. Similarly, groups with higher minimum MAOs failed to complete more rounds. Specifications 1-4 were fit using logistic regression; specifications 5-6 were fit using OLS regression. Coefficients are standardized and group-clustered standard errors are shown in parentheses.* *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Defaulted at any point		Defaulted in first round		Fraction of rounds foregone	
Group minimum MAO	0.64***	0.63**	0.61***	0.57*	0.09**	0.10*
	(0.24)	(0.28)	(0.22)	(0.34)	(0.04)	(0.06)
Condition (Social dilemma=1)	1.59***	1.60***	1.31***	1.29***	0.28***	0.27**
	(0.48)	(0.53)	(0.44)	(0.44)	(0.07)	(0.07)
Group minimum MAO x Condition		0.03		0.06		0.04
		(0.54)		(0.45)		(0.08)
Constant	0.39	0.39	1.32***	1.30***	0.54***	0.54***
	(0.28)	(0.28)	(0.33)	(0.35)	(0.06)	(0.06)
Observations	120	120	120	120	120	120
R-squared/Pseudo R-squared	11.8%	11.9%	9.2%	9.2%	12.2%	12.4%

Thus, our Microloan Game results demonstrate that the positive relationship between UG MAO and microcredit defaults shown in the cross-cultural data extends to the much more controlled environment of a laboratory game using just American participants, and applies at the level of individual psychology (rather than, for example, just tracking some other group-level cultural trait in the cross-cultural dataset). That is, although there are clear identification issues with the model we fit to the cross-cultural data in the previous section, the fact that we observe the same pattern in the lab at the individual level supports our theoretical claim regarding inequity aversion and microloan default.

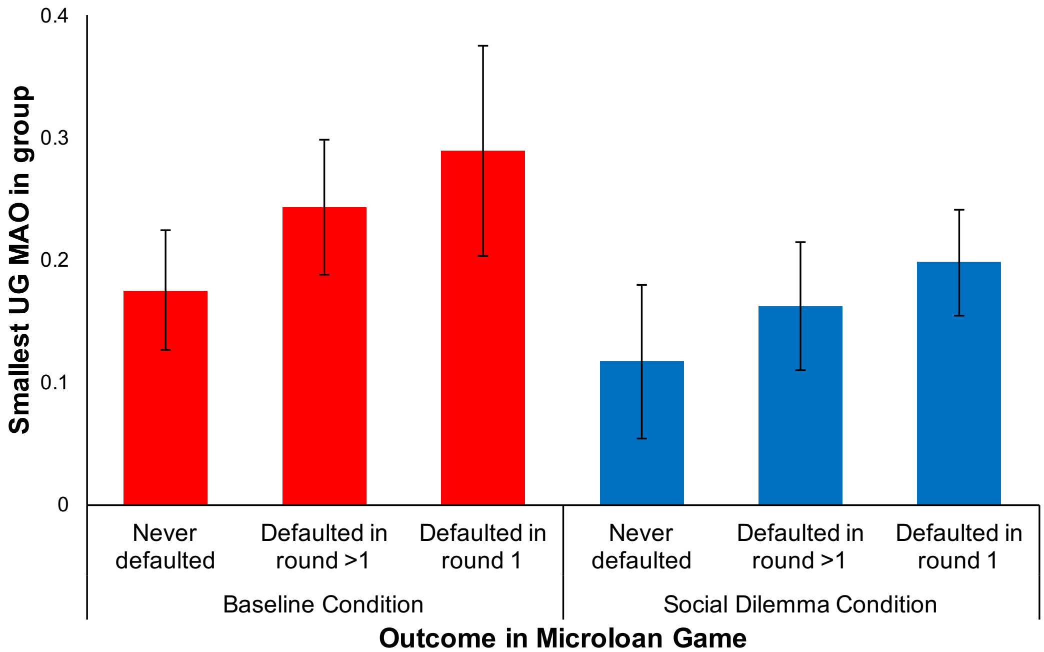

Figure 3. *Ultimatum Game MAOs are positively related to failure in the laboratory Microloan Game, both in the baseline and social dilemma conditions. Shown is the MAO of the least inequity averse group member (i.e. group member with the lowest MAO) average across all groups who either never default, did not default in the first round but eventually defaulted in a later round, or defaulted in the first round; groups from the baseline condition are shown in red, and from the social dilemma condition in blue. Error bars indicate 95% confidence intervals.*

While the results from this individual-level experiment are what we expected based on our inequity aversion model of the microloan interaction, there are limitations of the experiments that are important to acknowledge. We noted above that we stripped away some important features of solidarity group lending in an effort to isolate the role of inequity aversion in the microloan interaction. In particular, we did not allow participants to track the behavior of specific individuals (which would have made negative reciprocity possible), and we did not allow communication. By removing these features from the interaction, we were able to isolate the role of inequity aversion, but removing such features also has the potential to reduce the external validity of the experiment. Furthermore, our main goal in this experiment (and in the model described above) was to compare the behavior of money-maximizers and those who are inequity averse, but other motivators are likely to also play a role (e.g. altruism). Furthermore, the subjects used in our experiment (Americans on MTurk) are quite different in many ways from typical participants in microloans. Future work should explore how inequity aversion interacts with reciprocity and communication in microloans, the role of other motivations for default, and the generalizability of results beyond our particular subject pool.

We would also like to note some other limitations of this work raised during the review process. For example, because the MIX does not contain loan methodology, our microfinance outcomes come from banks that use a variety of loan types, some of which do not use joint liability. While this should only make our estimates of the relationship between inequity aversion and default more conservative, it is worth noting nonetheless. It is also the case that many of the variables we pulled from the WVS include responses from demographics that are not the target for microloans; namely the rural and working poor. Similarly, while our measure of default (PAR 30) is a useful proxy, having a longer-term at-risk measure would be helpful to test the longevity of inequity aversion (i.e., given sufficient time, do inequity averse individuals cool-off and eventually pitch in?).

Discussion

Here we have provided evidence that a key determinant of the success of solidarity group lending—the predominant model of microlending—is people's willingness to overcome inequity aversion and pitch in when other group members fail to make their payments. As such, we find that variation in inequity aversion (as measured by UG rejections) and not variation in cooperativeness (captured by a variety of measures) is strongly predictive of default rates across countries. In addition, this relationship is also evident in the psychology of individuals: in a laboratory model of microcredit, groups with individuals having higher UG MAOs (i.e., more inequity averse) are more likely to default.

Our observation that the psychology of inequity aversion plays such an important role in driving defaults rates has important policy implications. With this perspective, it becomes possible to leverage the large body of work in behavioral economics regarding the motivations of UG rejection to design default-reduction interventions.

For example, there is considerable evidence that "cool-off" periods, in which responders are asked to wait for several minutes or overnight before responding to offers, dramatically reduce rejections in the UG (Oechssler et al. 2013; Grimm & Mengel 2011; Neo et al. 2013; Oechssler et al. 2015; Wang et al. 2011). Instituting an analogous cool-off period for borrowers at risk of defaulting would be easy to do and free to implement: in the event that a borrower cannot make her payment, either during the course of repayment or at the end of the loan period, the loan officer would leave and return the next day once the group has had a chance to cool-off and consider the consequences of not pitching in. If such an intervention were to be successful in reducing avoidable defaults, microfinance institutions would stand a better chance of becoming self-sustaining.

Secondly, it has been shown that reputation concerns can provide a rationale for rejecting in the UG, in order to induce others to offer more in the future (Fehr & Fischbacher 2003). Thus, it may be advantageous for microfinance institutions to minimize the opportunity for such incentives. For example, to the extent that borrowers who refuse to pitch in do so because they don't want to be seen as the kind of person who can be taken advantage of (Thaler 1988), allowing borrowers to pitch in for others' loans anonymously would allow for those who want to help others to do so without any reputational repercussions. In general, any procedural change that removes cues to reputation for the pitching in phase (but not the initial contribution phase) should retain the feature necessary for avoiding free-riding while reducing the motivation to hold out when pitching in is possible.

In the decades since the solidarity group model of microlending came into existence, it has spread to many millions of borrowers in most of the world's developing nations. But this spreading didn't take into account the psychological variation across societies, and the one-size-fits-all approach to microlending has run into sustainability issues (Hermes & Lensink 2011). Microfinance institutions, and therefore their borrowers, stand to benefit from a deeper understanding of the psychology that makes microcredit work where it works and fail where it fails.

Human subjects approval

These studies complied with all ethical regulations for the use of human subjects, and approval for the study was provided by the Human Subject Committee at Yale University.

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Supplementary Information

Additional analyses: empirics

Yearly country-level analyses

Table S1. Ultimatum Game rejection rates, not offers, predict defaults

	2007	2008	2009	2010	2011	2012	2013	2014
VARIABLES				Portfolios at risk				
Offers	0.112	0.206	0.130	0.114	0.120	0.0684	-0.0668	-0.164
	(0.217)	(0.158)	(0.133)	(0.259)	(0.142)	(0.173)	(0.357)	(0.278)
Rejections	0.282*	0.215*	0.507***	0.432**	0.318***	0.0530	0.683**	0.426**
	(0.137)	(0.100)	(0.0841)	(0.165)	(0.0899)	(0.111)	(0.228)	(0.176)
Constant	-0.00650	-0.0277	-0.000869	-0.00600	-0.000738	0.0331	0.0422	0.106
	(0.0857)	(0.0624)	(0.0524)	(0.103)	(0.0560)	(0.0689)	(0.142)	(0.110)
Observations	12	12	12	13	12	13	13	12
R-squared	34.8%	44.2%	81.4%	42.3%	61.2%	4.1%	47.3%	39.9%

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

Table S1 above shows that in each year (except 2012), UG rejection rates are highly predictive of default rates while offers are not. When we excluded Papua New Guinea, rejection rates were still predictive, β = 0.238, SE = 0.092, p = 0.030, R^2 = 43%, and offers remained unpredictive, β = 0.074, SE = 0.130, p = 0.605, R^2 = 5%. Further, there is no World Values Survey trust index data for Papua New Guinea, which means that specifications 2-10 of Table S2 all exclude Papua New Guinea, yet still replicate the relationship between UG rejection rates and default rates. Further, for those concerned that including both offers and rejection rates in the same model is problematic, our results hold when we examine either independent variable on its own. In particular, collapsing across the 8-year period, we find no effect of UG offers on default rates, β = 0.128, SE = 0.210, p = 0.555, R^2 = 3%, but a strong effect of UG rejection rates, β = 0.367, SE = 0.130, p = 0.080, R^2 = 66%.

Bank-level analyses

Table S2. Bank-level analysis predicting defaults using Ultimatum Game play

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					Portfolios at risk					
Offer	0.0962	0.0517	0.0465	0.0801	0.0582	0.0296	0.0756	-0.0343	0.0787	0.0593
	(0.104)	(0.0938)	(0.102)	(0.0941)	(0.0999)	(0.0972)	(0.0886)	(0.0949)	(0.0905)	(0.0365)
Rejections	0.433**	0.232**	0.257***	0.236**	0.252***	0.228***	0.251***	0.321****	0.198**	0.233****
	(0.134)	(0.0870)	(0.0707)	(0.0816)	(0.0655)	(0.0651)	(0.0652)	(0.0759)	(0.0633)	(0.0280)
WVS trust		0.0417	0.0327	0.0265	0.0205	0.0353	0.0317	0.0849***	0.00897	-0.0351
		(0.0217)	(0.0222)	(0.0195)	(0.0236)	(0.0205)	(0.0212)	(0.0229)	(0.0316)	(0.0549)
% female			-0.0902**	-0.0959*	-0.0905**	-0.0900**	-0.0896**	-0.0912**	-0.0971*	-0.0982*
			(0.0311)	(0.0399)	(0.0315)	(0.0308)	(0.0313)	(0.0282)	(0.0399)	(0.0390)
Yield				0.0252					0.0274	0.0352
				(0.0405)					(0.0411)	(0.0565)
GDP (trillions)					0.0163				0.0323	0.206**
					(0.0132)				(0.0231)	(0.0720)
GDP growth (%)						-0.00307*			-0.00295*	-0.00310*
						(0.00124)			(0.00125)	(0.00149)
GDP/cap (millions)							1.369		-0.176	-1.692
							(2.247)		(1.619)	(1.935)
Gini								0.000173		0.000636
								(0.00116)		(0.000996)
Constant	0.00209	0.0212	0.0735	0.0582	0.0710	0.0983*	0.0571	0.0738	0.0797*	0.0529
	(0.0436)	(0.0343)	(0.0440)	(0.0406)	(0.0433)	(0.0427)	(0.0389)	(0.0622)	(0.0392)	(0.0515)
# of MFIs	1,553	1,531	1,247	1,180	1,247	1,247	1,247	913	1,180	883
# of Countries	13	12	12	12	12	12	12	10	12	10
R-squared	8.3%	7.1%	11.9%	14.6%	12.1%	12.5%	12.0%	16.8%	15.8%	21.2%

Country-clustered robust standard errors in parentheses

**** p<0.0001, *** p<0.001, ** p<0.01, * p<0.05

Table S2 above shows that UG rejection rates, at the country level, are robustly predictive of bank-level defaults rates. The fact that the UG rejection rate in each country is importantly predictive of default rates at the bank level suggests that it is the resident psychology of the borrowers, not administrative quirks of MFIs, that is driving defaults. This pattern of results hold if we omit UG offers, as was the case in the last set of regressions.

There are a few main results to note in this regression table. First, UG rejection rates are robustly predictive after controlling for economic development indicators (specifications 9 and 10).

Second, by and large, the developmental indicators are not strong predictors of default, which suggests that there is something other than economic conditions that is driving defaults. Third, loan yield—a proxy for interest rates—is not predictive of default rates over and above the controls in specification 4. (Interestingly, loan yields are not predictive of defaults rates within a given MFI, $\beta = -0.005$, SE = 0.007, $p = 0.419$.) Fourth, the next best predictor of defaults after Ultimatum Game rejection rates is the percentage of borrowers that are female. This is a nice replication of one of the early studies done trying to understand default rates and how group dynamics promote or avoid defaults.

Cross-cultural surveys, game play, defaults, and economic controls

Using a separate meta-analysis of cross-cultural differences in Trust Game behavior, in addition to Ultimatum Game behavior we were able to look at the relationship between trust, trustworthiness, and default rates. In Table S3 below, we show the relationships between behavior in the Ultimatum Game, Trust Game, WVS trust, WVS civic cooperation, democracy, corruption, and rule of law after controlling for the economic development status of the country. The analysis in Table S3 reflects country-level outcomes and is restricted to 2007 to 2014.

Table S3. Game play and survey variables predicting default rates with economic controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Portfolios at risk								
UG rejection rate	0.4610**								
	(0.0958)								
UG offers		0.1660							
		(0.3753)							
TG % sent			0.1189						
			(0.0629)						
TG % returned				0.1195					
				(0.0552)					
WVS trust					-0.0328				
					(0.0442)				
WVS civic cooperation						0.0059			
						(0.0083)			
Democracy rank							-0.0000		
							(0.0003)		
Corruption rank								0.0004	
								(0.0003)	
Rule of law									-0.0192
									(0.0166)
GDP growth (%)	0.0058	-0.0021	-0.0048	-0.0125	-0.0019	-0.0013	-0.0084*	-0.0078	-0.0059
	(0.0061)	(0.0140)	(0.0071)	(0.0057)	(0.0050)	(0.0057)	(0.0042)	(0.0042)	(0.0039)
GDP (trillions)	0.0282	-0.0132	0.0049	0.0004	-0.0007	-0.0065	-0.0124	-0.0148	-0.0120
	(0.0495)	(0.1200)	(0.0120)	(0.0116)	(0.0225)	(0.0229)	(0.0244)	(0.0242)	(0.0239)
GDP per capita (millions)	4.6645	1.5217	-2.5720	-4.2209	4.8308	5.1265	0.1022	2.4505	2.5760
	(3.2669)	(8.4529)	(2.1887)	(2.0655)	(2.6649)	(2.8815)	(2.9732)	(3.0689)	(2.9128)
Gini	0.0011	-0.0016	0.0001	0.0008	-0.0010	-0.0009	0.0013	0.0014	0.0013
	(0.0014)	(0.0030)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0009)	(0.0009)	(0.0009)
Constant	-0.0760	0.0981	0.0448	0.0771	0.1063	0.0737	0.0660	0.0182	0.0340
	(0.0946)	(0.2499)	(0.0748)	(0.0624)	(0.0548)	(0.0489)	(0.0548)	(0.0566)	(0.0431)
Observations	11	11	15	15	45	42	71	71	76
R-squared	83.4%	10.0%	49.0%	53.2%	14.6%	14.9%	9.5%	11.7%	8.6%

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

The only variable that is robustly predictive of defaults rates after controlling for economic development status are Ultimatum Game rejection rates, which is positively related to defaults. On the social capital account of repayment, trustworthiness should be negatively related to default rates. Note that GDP is in trillions for ease of interpreting coefficients, but using the raw GDP does not change the result.

Experiment

Recruiting and Ultimatum Game

Participants for the experiment were recruited through Amazon's Mechanical Turk. We recruited only participants from the US. Participants first learned about the Ultimatum Game from the instructions below:

> In this interaction you are matched with one other person.
> One of you will be person A, one of you will be person B.
> Person A starts with 200 units and person B starts with 0. For this interaction, and those that follow, units will be converted at the end of the study to real dollars. Specifically, for every 10 units you earn you will receive 1 cent.
> *First person A makes a choice, then person B responds.*
> 1) Person A will make an offer on how to split the 200 units with person B.
> 2) Person B will either *accept* or *reject* this offer.
> *If* person B *accepts,* then B will get the offered amount and A will keep the rest.
> *If B rejects the offer then both individuals will get 0 units.*

Participants then answered a set of comprehension questions about the Ultimatum Game while they still had access to the instructions. The comprehension questions are below:

> 1. What choice by Player A will result in Player A earning the most money?
> [Player A offering Player B nothing, Player A offering Player B everything, It depends on what the receiver is willing to accept]
> 2. Which choice by Player B will result in Player B earning the most money?
> [Player B deciding to accept the offer, Player B deciding to reject the offer]
> 3. If Player B decides to accept Player A's offer, what happens?
> [Each Player's bonus is determined by Player A's offer, Each Player gets a random bonus, Both Players get no bonus]
> 4. If Player B decides to reject Player A's offer, what happens?
> [Each Player's bonus is determined by Player A's offer, Each Player gets a random bonus, Both Players get no bonus]

Once participants had passed the comprehension test, we elicited their MAO. They could choose in 10-unit increments between 0 and 200. After they had reported their MAO, they reported what they would offer, using the same increments as the MAO.

Baseline and Social Dilemma Interactions

After the Ultimatum Game, participants moved onto the main portion of the experiment. They were randomly assigned to a group with 2 other people and each group was randomly assigned to either the Baseline condition or the Social Dilemma condition.

Below are the instructions and comprehension questions for the Baseline condition:

> You have been assigned to a group with 2 other people. You each will have the opportunity to earn units over a series of rounds of play, which will be converted to real money at a rate of 10 units per cent.
> Each of you will be assigned an identifier, but these identifiers are randomly shuffled each round. Thus you will not be able to track the behavior of the other people from round to round.
> Each round works as follows:
>
> 1) Each of you receives a randomly determined number of units, between 0 and 500. Each of you may receive a different amount. You do not know the amounts received by the other group members, and they do not know the amount you receive.
> 2) You each choose how many of these units to keep toward your bonus, and how many to contribute to the group. In order to continue to the next round, each person must contribute 200 units to the group. Otherwise, the game ends and none of you have a chance to earn additional money, unless a group member 'pitches in' in stage 3.
> 3) If anyone in your group contributes *less* than 200 units, the group is told how many additional units are needed to meet the 200-unit-per-person threshold. Then each of you in turn can choose whether (or to what extent) to 'pitch in' and make up the difference by contributing more than 200 units yourself.
> 4) If the threshold is met, your group will continue to the next round. Your group will play at least 8 rounds. After the 8th round, there is a 50% probability that there will be another round, and another, and so on. If the threshold is not met, the game ends immediately and none of you have a chance to earn any further bonus money.

Participants then answered the following comprehension questions and if they failed one or more (in either condition) they were excluded from the remained of the study.

1) Might you receive a different amount of starting money in each round than other people in your group? [Yes / No]
2) How many units are you responsible for contributing each round? [100, 200, 300, 400, 500, 600]
3) If you or someone in your group does not make their full contribution, what happens? [the game ends immediately; nothing happens and the game continues to the next round; other group members can 'pitch in' and make up the difference in that player's contribution]
4) After the 'pitching in' phase is over, if you or someone in your group has failed to contribute enough units to get over the 200 unit threshold, what happens? [the game ends immediately; nothing happens and the game continues to the next round; everyone gets a bonus unit]

Below are the instructions and comprehension questions for the Social Dilemma condition:

> You have been assigned to a group with 2 other people. You each will have the opportunity to earn units over a series of rounds of play, which will be converted to real money at a rate of 10 units per cent.

Each of you will be assigned an identified, but these identifiers are randomly shuffled each round. Thus you will not be able to track the behavior of the other people from round to round.
Each round works as follows:

1) Each of you receives a randomly determined number of units, between 0 and 500. Each of you may receive a different amount. You do not know the amounts received by the other group members, and they do not know the amount you receive.
2) You each choose how many of these units to keep toward your bonus, and how many to contribute to the group. In order to continue to the next round, a total of at least 600 units must be contributed to the group. Otherwise, the game ends and none of you have a chance to earn additional money.
3) If less than 600 units are contributed, the group is told how many additional units are needed to meet the 600-unit threshold. Then each of you in turn can choose whether to 'pitch in' and make up the difference by contributing more, unless a group member 'pitches in' in stage 3.
4) If the threshold is met, your group will continue to the next round. Your group will play at least 8 rounds. After the 8th round, there is a 50% probability that there will be another round, and another, and so on. If the threshold is not met, the game ends immediately and none of you have a chance to earn any further bonus money.

After reading the instructions, participants in the threshold condition answered the following comprehension questions.

1) Might you receive a different amount of starting money in each round than other people in your group? [Yes / No]
2) How many units is your group responsible for contributing each round? [100, 200, 300, 400, 500, 600]
3) If your group does not make its full contribution, what happens? [the game ends immediately; nothing happens and the game continues to the next round; the group members can 'pitch in' and make up the difference]
4) After the 'pitching in' is done, if your group failed to contribute enough units to get over the 600 unit threshold, what happens? [the game ends immediately; nothing happens and the game continues to the next round; everyone gets a bonus unit]

Regression table

Below is a regression table that shows the regression results from the three sets of statistical models we fit. Specifications 1-4 are fit using logistic regression, while specifications 5 and 6 are fit using OLS regression. For each specification, we use the lowest MAO in the group in order to capture the how inequity averse the group's least inequity averse member was. Groups with lower minimum MAOs have at least one member who will be more willing to pitch in, while groups with high minimum MAOs are less likely to have a member who will be willing to pitch in.

Table S4. Regression results from the experimental data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Defaulted at any point		Defaulted in first round		Fraction of rounds foregone	
Group minimum MAO	4.719***	4.655**	3.952***	3.713*	0.636**	0.747**
	(1.766)	(2.057)	(1.451)	(2.219)	(0.286)	(0.361)
Condition (Social dilemma=1)	1.590***	1.554**	1.305***	1.194	0.276***	0.327**
	(0.484)	(0.763)	(0.437)	(0.898)	(0.074)	(0.132)
Group minimum MAO x Condition		0.245		-0.412		0.264
		(4.017)		(2.929)		(0.558)
Constant	0.553	0.539	2.261***	2.186***	0.665***	0.690***
	(0.462)	(0.512)	(0.551)	(0.759)	(0.081)	(0.0972)
Observations	120	120	120	120	120	120
R-squared/Pseudo R-squared	11.8%	11.9%	9.2%	9.2%	12.2%	12.4%

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1