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Cooperation and Expectations in Networks

Evidence from a Network Public Good Experiment in Rural India*

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Abstract

We play a one-shot public good game in rural India between farmers connected by an exogenous star network. Contributions by the centre of the star reach more players and have a larger impact on aggregate payoffs than contributions by the spoke players. Yet, we find that the centre player contributes just as much as the average of the spokes. We elicit expectations about the decisions of the centre player and, in randomly selected sessions, we disclose the average expectation of the farmers in the network. Farmers match the disclosed values frequently and do so more often when the monetary cost of making a contribution is reduced. However, disclosure is not associated with higher contributions. Our results support the predictions of a model of other-regarding preferences where players care about the expectations of others. This model is helpful to understand barriers to improvement in pro-social behaviour when groups expect low pro-sociality.

1 Introduction

We study the provision of public goods in a star network among farmers in rural India. The experimental literature has long recognised that heterogeneity in individual characteristics affects the level and dynamics of cooperation in human groups [Ledyard, 1995, Reuben and Riedl, 2013]. Social networks where individuals are asymmetrically connected create heterogeneity on a number of dimensions. Take the example of the production of information about new technologies. When the quality of this information deteriorates quickly with each relay in the network, only individuals who are socially proximate to the innovators are able to benefit from the investments in new knowledge [Bramoulle and Kranton, 2007]. Alternatively, monitoring and punishment of free-riders is sometimes possible only along the lines of existing social relations. These types of network-based heterogeneities are likely to be particularly relevant for farming communities in the developing world. Peer learning is known to occur frequently in these communities and the evidence reported in a number of studies suggests that free riding on the experimentation efforts of one's neighbours is common [Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006]. As farmers face substantial informational barriers to the adoption of new technologies [Jack, 2013], high levels of cooperation in local innovation networks can improve technology uptake and reduce rural poverty.

In this paper we explore whether the player at the centre of the star is influenced by the level of contributions to the public good that individuals in the network expect him to make. Behavioural game theory hypothesises that individuals want to avoid the feeling of guilt, which they experience when they determine a payoff for other players that is lower than what these players expect [Battigalli and Dufwenberg, 2007].[1] Thus, in a public good game, a guilt averse player contributes to the public good as much as others expect him to contribute. There are important implications that follow from this. Depending on the distribution of expectations in the population, guilt aversion can be an equally powerful force for the promotion of pro-social behaviour or for the persistence of low pro-sociality. Further, when guilt aversion is diffused, within-individual variation in pro-sociality across contexts can be high, increasing the scope for policy interventions that move groups to superior equilibria.

In our experiment, as in standard public good games, individuals are given an initial endowment that has to be allocated between a private account and investment

[1]We give a formal definition of guilt aversion in section 3.

in a public good. Contributions to the public good increase aggregate payoff, while decreasing the payoff of the contributor. As explained above, following the model of Bramoulle and Kranton [2007], the star network determines who can benefit from the public good contributions of a particular player. The contributions of the centre of the star thus reach more individuals and have a larger impact on the total welfare of the group than the contributions of the spoke players.[2] We focus the analysis on the behaviour of farmers when they are placed at the centre of the star. High-degree players in networks, whose actions affect the payoffs of a large number of individuals, may in fact be particularly concerned with guilt. Theory and evidence in social psychology suggests that guilt aversion has its roots in the fear of exclusion from a reference group [Baumeister et al., 1994]. Such fear is likely to heighten as the number of affected individuals increases.

We use the strategy method twice. First, to elicit contribution decisions for both the case where the player is assigned to the centre position and the case where the player is assigned to the spoke position. Second, to allow the centre of the star to contribute different amounts depending on the average contribution of the spokes. We collect players' expectations about how much other players will contribute when they are deciding as centre of the star.[3]

In our main treatment we disclose the average value of the expectations of the players in the network.[4] This captures what farmers in the experimental session, on average, expect the centre of the star to contribute. Sufficiently guilt averse individuals will contribute as much as the group expects them to contribute. They will do so more frequently as the monetary cost of contribution is decreased. We

[2]This type of heterogeneity has some similarities with heterogeneity in the rate of return to contributions, which is explored, for example, in the experiments of Reuben and Riedl [2009] and Nikiforakis et al. [2012]. It also has two crucial differences. First, in our set-up, the monetary loss that the centre player incurs to make one unit of contribution is the same as that incurred by a spoke player. On the other hand, high rate of return players suffer a less severe payoff loss than low rate of return players when they invest in the public good. Second, the centre of the star is more efficient at increasing aggregate welfare than the spokes because *a higher number of players benefit from his contributions*. High rate of return players, on the other hand, are more efficient at increasing aggregate welfare because their contributions have *a greater effect on each of the other players* .

[3]The centre of the star has to specify a contribution level for each of four possible (rounded) average contribution levels of the spokes. We thus elicit expectations about the average contribution in each of the four decisions.

[4]Throughout the paper, we will refer to these as "group expectations". We disclose the average value of each of the four forecasts that players make. See footnote 3.

thus cross-cut this treatment with random variation in the parameter that affects the monetary cost of contribution and perform a statistical test of the model's prediction. In two final treatments, we attempt an experimental manipulation of expectations. Only half of the individuals in a session are affected. The objective is to generate exogenous variation in the average value that we disclose, allowing us to test a further prediction of the model of guilt aversion on the second half of players: contributions will be higher (lower) when the average expectation that we disclose is higher (lower).

Our first finding is that, in the baseline treatment, the centre of the star contributes an amount that is close to the average contribution of the spokes. This is what the literature calls "conditional cooperation", a strategy that has often been documented in public good games played by homogeneous groups [Fischbacher et al., 2001]. The finding is supported by regression analysis and by the relative frequency of the strategies chosen by players. Moreover, farmers on average expect the centre of the star to be a conditional cooperator. This confirms the focality of this strategy in the game. While not systematically biased, expectations are often inaccurate.

The average contribution of the spokes is about half of the endowment. Given conditional cooperation, the centre of the star contributes a similar amount. As a result, farmers in the baseline treatment are able to capture only about 50 percent of the potential gains from cooperation.

When we disclose the average expectations of the players in the network, we find a match between contributions and disclosed values in 42 percent of decisions. We increase the rate of return to investments in the public good and thereby lower the *monetary cost* of contributions. For high understanding players, the frequency of matches between contributions and group expectations significantly increases to 53 percent. This is our second main finding which confirms the prediction of the model of guilt aversion. Interestingly, the effect is moderated by the average degree in the real-life network that connects individuals in a session. Farmers in more connected networks experience larger increases in the frequency of matches between contributions and group expectations. We are unable to find further statistically significant effects of this treatment on the *level* of expectations, or on the frequency of matches between contributions and *individual* expectations.[5] This helps us to rule out alternative mechanisms that could be explaining our finding.

[5] These are expectations about what other players in the session would contribute when they are in the position of the centre of the star.

Contributions match average group expectations less often (6-7 percentage points) when we do not disclose the true average, suggesting that a number of farmers may have inaccurate priors about the average group expectation in their session. However, aligning contributions to group expectations does not result in greater investments in the public good from the centre of the star. This is a third important finding, suggesting that the provision of information about current expectations is insufficient to improve outcomes in our setting.

Our last result is that the manipulation of expectations that we attempt is weak. At the session level, the average group expectation that we disclose is not significantly affected by this last treatment. We are thus unable to provide a fair test to the second prediction of the model of guilt aversion.

The literature offers both theoretical and experimental analyses of public good games played over networks. The games that have been proposed differ on at least three dimensions: whether the network determines the reach of contributions or the observability of players' actions; whether the payoff function implies an interior optimum or a corner solution; whether play is one-shot or repeated. Bramoulle and Kranton [2007] study equilibria and welfare in a game where the network determines the reach of contributions, the optimum is interior and players have no social preferences. Their seminal analysis highlights the potential for specialisation in networks. Rosenkranz and Weitzel [2012] play a repeated version of their game and document that coordination on theoretical equilibria is infrequent and unstable.[6] Other studies find that when links determine observability, the structure of the network influences the level of cooperation [Fatas et al., 2010, Carpenter et al., 2012].[7]

We contribute to this literature by offering a design that is particularly amenable to a study of other-regarding preferences. The strategy method, which to our knowledge we apply for the first time to a public good game played over a network, removes uncertainty about the distributional consequences of actions and the history of play. The payoff function determines a corner solution at zero for rational selfish players, making deviations from selfish best response transparent and easy to analyse. The

[6] Only 2.4 percent of decisions are part of a theoretical equilibrium, and episodes of convergence to an equilibrium occur in 27 periods over 3360.

[7] There is also a small literature that studies prisoner dilemma games over networks, which is discussed in Kosfeld [2003].

network structure creates salient asymmetries across network positions regarding the effects of contributions on the welfare of other players.

Since the widely cited study of Fischbacher et al. [2001], the strategy method has often been employed in public good games played by homogeneous groups. A widely reproduced finding is that a large fraction of players are "conditional co-operators" [Gaechter, 2006, Chaudhuri, 2011]. These are defined as players whose "contributions to the public good are positively correlated either with their ex ante beliefs about the contributions to be made by their peers or to the actual contributions made by the same" [Chaudhuri, 2011, p.56]. In our study, we show that conditional cooperation is followed by the centre player of a highly asymmetric star network.[8] This extends our understanding of the settings where this behaviour occurs and highlights the importance of incorporating other-regarding motives in existing models of public good provision over networks.

The other-regarding preference that we focus on in this paper is guilt aversion. As explained above, guilt averse players dislike to play strategies that generate a payoff for the other players that is lower than the payoff these players expect. A formal definition of guilt aversion is given by Battigalli and Dufwenberg [2007]. Empirical evidence in support of this model of utility is provided in the trust games played by Dufwenberg and Gneezy [2000], Charness and Dufwenberg [2006], Bacharach et al. [2007] and Reuben et al. [2009], and in the public good game played by Dufwenberg et al. [2011]. Bellemare et al. [2010] estimate that Dutch individuals drawn from a representative sample are "willing to pay between 0.40 and 0.80 Euro to avoid letting down proposers by 1 Euro". On the other hand, Ellingsen et al. [2010] are unable to find evidence in support of guilt aversion among Swedish students.

We provide statistically significant evidence in support of the first prediction that the model of guilt aversion makes for our game.[9] This result is a contribution to the literature that assesses the behavioural relevance of guilt aversion and to the social networks literature. It importantly suggests that strategic behaviour in networks is at least partly influenced by contextual expectations and not just by fixed,

[8]For a public goods game played over a network, Fatas et al. [2010] report a positive correlation between current contributions and the contributions of peers in previous rounds. They interpret this correlation as suggesting conditional cooperation, as peer past contributions are probably a major determinant of a player's expectations about current contributions.

[9]As explained, as our experimental manipulation of beliefs is weak, we cannot test the second prediction.

underlying distributional preferences. We also document that the average degree connecting in real-life the individuals that take part in the experiment positively moderates the effect of guilt aversion. This suggests that experiments that recruit subjects from loosely connected, large groups provide only a lower bound estimate of the extent to which guilt aversion can motivate human behaviour in more tightly connected communities.

Finally, our work is related to the literature on the elicitation of expectations. Economists often ask individuals to report point and probabilistic forecasts of uncertain events [Manski, 2004]. The experimental literature has imported these techniques to study expectations in strategic settings. Several applications elicit individual expectations about the *strategies* chosen by other players, while a small number of studies explore individual expectations about the *expectations* held by other players [Manski and Neri, 2013].[10] In recent years, expectation elicitation techniques have also been used with success with low average education populations in developing countries [Delavande et al., 2011]. This strand of work has restricted attention to non strategic environments: for example, the returns to schooling, the benefits of new technologies, the prices of agricultural products. On the other hand, evidence from developing economies about the expectations of subjects in strategic settings is scarce. An exception is Caria and Falco [2014], who report that employers in urban Accra have inaccurately pessimistic priors about the trustworthiness of a sample of employees. On the contrary, we find that, on average, farmers correctly expect the centre of the star to play conditional cooperation. We contribute to this literature by showing that within our novel strategic setting and a population of farmers who interact with each other with high frequency, expectations are not systematically biased. This limits the potential for interventions that align priors to true values.

In the next section we present the design of the experiment. Section 3 develops a number of predictions and discusses how we will formulate the related statistical tests. Section 4 outlines the data we use and the basic descriptives. Results are presented and discussed in section 5. Concluding remarks are included in the final section of the paper.

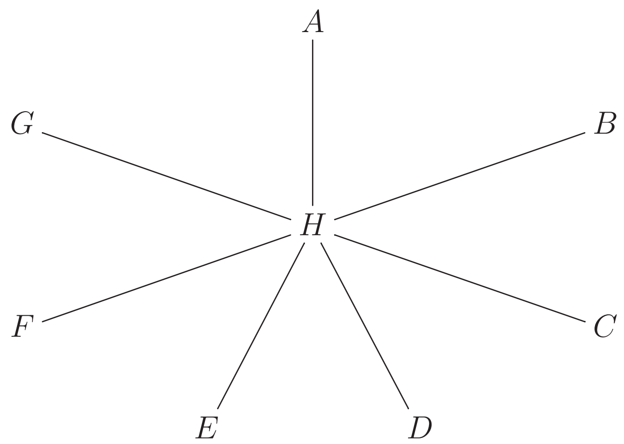
[10] The literature in behavioural game theory calls expectations about the strategies of other players "first order expectations". "Second order expectations", on the other hand, are expectations about the first order expectations of the other players.

2 Design

We play a public good game between players connected by a network. The network determines who benefits from the public good contribution of a particular player.

In each session we recruit 8 participants. These will eventually be arranged over a star network like the one represented in picture 1 below. Links in this network cannot be changed and are undirected: if A is linked to H, then H is linked to A. There are two types of players: one centre and seven spokes. The centre benefits from the public good contributions of the seven spokes. Further, his own contribution reaches each of the spokes. A spoke, on the other hand, only receives the contribution of the centre and only reaches the centre with his own contribution. The position of each farmer in the network is randomly assigned *after* all contribution decisions have been made.

Figure 1: The star network



2.1 Contributions

Each player is endowed with 3 notes worth 50 INR each and has to decide how many notes to contribute for the provision of the public good. As players' position in the network is assigned *after* the contributions decisions are made, we ask player to specify in advance how much they would like to contribute if they will be assigned to (i) the spoke position and (ii) the centre position. Decision (i)- we call this the "spoke contribution"- is an unconditional contribution decision. s_i indicates the "spoke contribution" of player i. On the other hand, decision (ii)- we call this the "centre contribution"- is conditional on the average of the spokes. There are 4 possible (rounded) average contribution levels of the spokes: 0,1,2 and 3 notes. For each possible average contribution level z, player i has to declare how much he would like to contribute if he is assigned to the centre position *and* the seven spokes have contributed on average z. The conditional contribution decision of player i when spoke average contribution is z is called c_i^z. The vector $c_i = \left(c_i^0, c_i^1, c_i^2, c_i^3\right)$ collects the four conditional decisions of player i. We call c_i^z a contribution "decision" and c_i a contribution "profile".

After positions are assigned, the enumerator calculates the (rounded) average of s_i for the seven players assigned to the spoke position. Given this average, the enumerator selects the right element from the c_i vector of the player assigned to the centre position. Let x_i indicate the actual number of notes that player i contributes to the public good: $x_i = s_i$ if player i is a spoke and $x_i = c_i^z$ if player i is the centre and the average contribution of the seven spokes is z.

Using notation from Goyal [2012], we define N as the set of players in a session, and N_i^d as the subset of these players that are linked to player i. The payoff of player i at the end of the game is given by:

$$\pi_i = 50(3 - x_i) + r50\left(\sum_{j \in N_i^d} x_j + x_i\right) \quad r = \{3/5, 4/5\} \tag{1}$$

The rate of return "r" to investing in the public good can take a low (3/5) or a high (4/5) value. Experimental sessions are randomly allocated to a high or a low value of r.

Three features of this design are worth noting. First, the payoff function 1 resembles closely the standard payoff function of public good experiments [Camerer, 2003, Chaudhuri, 2011]. The only difference is that we sum over the contributions of the direct connections N_i^d and not over the contributions of all players N. The main strategic features of a public good game are preserved. First, $r < 1$ and hence contributing a positive amount is a dominated strategy. Second, when i increases his contribution by 1 note he forgoes 50 INR in private payoff, but generates a sum of individual payoffs equal to $r50(N_i^d + 1)$ INR. As $r(N_i^d + 1) > 1$ for all values of N_i^d in the star network, aggregate payoff monotonically increases in x_i and is maximised when everybody contributes the whole endowment.

Second, the impact of a note contributed by player i on the welfare of the other players- $r50N_i^d$- is proportional to the number of connections player i has. A note contributed by a spoke player has an impact of $r50$. A note contributed by a centre player has an impact of $r350$. The centre player is 7 times more efficient than the spoke player at generating payoff for the other players. This is a very high difference in efficiency.[11]

Third, the design relies twice on the strategy method. In the first instance, it allows players to specify a contribution decision for the case in which they are assigned to the spoke position and a second contribution decision for the case in which they are assigned to the centre position. Second, for the latter decision players are allowed to condition their contribution on the average contribution of the spokes. The strategy method has been employed frequently in public good games [Fischbacher et al., 2001, Brandts and Charness, 2011, Fischbacher et al., 2012]. It has been shown to produce qualitatively similar results to those observed using direct elicitation methods [Fischbacher et al., 2012] and all evidence so far shows that the choice between direct elicitation and strategy method does not influence whether a treatment effect is found or not [Brandts and Charness, 2011].

2.2 Expectations

Farmers have expectations about what "centre contribution" decisions c_i the other farmers will take. After the "spoke contribution" decision s_i is taken, but before "centre contribution" decisions c_i, we carry out two activities. These are meant, respectively, to elicit and to shock player i's expectations about the average of c among the other 7 players in the game.

First, we distribute a closed envelope to each player containing a message. In each session, there are 2 messages. Messages are randomly assigned and four players get each message. Players know the distribution of messages, but only see the content of the message that is assigned to them.

[11] Increasing the payoff of the other players is very cheap for the centre player. When $r = 4/5$, an additional note contributed by the centre player increases the payoff each other player by 40 INR (i.e. it increases total payoff by 280 INR), while decreasing the centre's own payoff by 10 INR. This ratio is even more favourable than in the "Barc2" and "Berk17" games played by Charness and Rabin [2002], where the player has to sacrifice 15 units of payoff in order to generate 350 units of payoffs for the other player. In the "Barc2" and "Berk17" games, about 50 percent of dictators choose to pay 15 units of payoff to increase the payoff of their experimental partner.

Some messages prime players to increase or decrease their expectations about what c decisions other farmers will take. The message that primes players to increases their expectation reads as follows: "Here is some information to help you with the expectation questions. Many farmers in your district have contributed 3 notes for every decision". The message that primes players to decrease their expectation is identical, but replaces 3 notes with 0 notes.[12]

Some messages are neutral. The first neutral messages reads "Thank you for taking part in this experiment". The second "We would like to thank your village for hosting this experiment". Details about the distribution of messages across sessions are given in the next sub-section which describes the treatments.

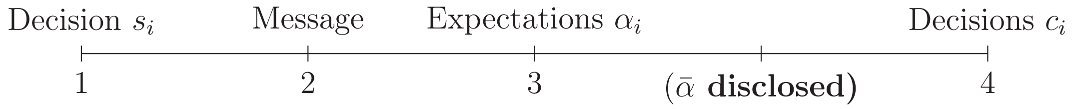
Second, each individual i is asked to guess what the average of c_j^z among the other 7 players will be, for each of the four possible values of z. We call this (point) expectation: α_i^z. More precisely: $\alpha_i^z = E_i\left(\sum_{j \in N \setminus i} \frac{c_j^z}{7}\right)$. For example, α_i^2 records how much player i expects the other 7 players to contribute *if* they are assigned to the centre position and the spoke average is 2. The vector $\alpha_i = \left(\alpha_i^0, \alpha_i^1, \alpha_i^2, \alpha_i^3\right)$ collects the four expectations of player i. We call α_i an expectation "profile".

Finally, $\bar{\alpha}^z$ is the average of α_i^z over all 8 players in N. In other words, $\bar{\alpha}^z$ indicates what is the contribution that individuals in the network, on average, expect from a player at the centre of the star when the spoke players have contributes an average of z notes. We refer to $\bar{\alpha}^z$ as the "average group expectation", or sometimes simply as the "group expectation". In some treatments, after eliciting α_i^z from each player i, we disclose $\bar{\alpha}^z$ publicly on a white board.[13] Disclosure comes as a surprise

[12] We do not quantify what we mean by "many". Non-trivial proportions of farmers indeed play either of these two strategies in the pilot. Hence this does not constitute a instance of lying, which is generally not allowed in economic experiments. A further concern is that the messages we distribute cannot be used by a Bayesian player to update his priors, as they do no constitute well specified signals with a known precision. While recognising this, we emphasise that our aim is to shock the beliefs of the sub-set of players that receive the priming messages. We conjecture that a well specified signal may in fact include too much information to be effective for real subjects. We hence rely on the simplest message, in the hope that it will have the best chance of modifying expectations. As it will become apparent in the results section, however, the message fails to change expectations systematically.

[13] This design feature makes the average expectation of the group clear and salient. However, it could be objected that disclosing any number could influence behaviour because of anchoring effects. To ensure differences in behaviour between T1 and T0 are not driven by anchoring effects, we could have reported 4 random numbers on the board in T0. We do not to include this feature to avoid confusing farmers (and enumerators) on the purpose of the random numbers.

Figure 2: Order of activities in the experiment



to subjects. This rules out the possibility that farmers mis-report their expectations in order to influence the behaviour of the other players.[14] It also rules out protocol differences before disclosure.

Figure 2 summarises the order of activities during the experiment. First, decisions s_i are taken for the case where i will be assigned to the spoke position. Second, messages are distributed. Third, expectations α_i are elicited. Then, in selected sessions, the average of expectations α_i is disclosed publicly. Finally, decisions c_i for the case where i will be assigned to the centre position are taken.

Before play, participants play a trial round of the game, which features steps 1 and 4 in figure 2, but does not include messages nor expectation elicitation. At the end of the trial round, the enumerator calculates the payoff that would accrue to participants given their decisions and a random draw that assigns positions in the network. This exercise reinforces participants' understanding of the game.

We choose not to incentivise the elicitation of expectations for a number of reasons. First, to keep the design simple. This is a priority given the difficulties involved in ensuring understanding of the strategy method and the expectation questions. Second, because, when we disclose $\bar{\alpha}$, other-regarding farmers may align their c_i decisions to the average belief $\bar{\alpha}$ in order to ensure that the other players are awarded the expectation incentive.[15] Third, to avoid hedging strategies. For example, a player may declare to have low expectations so that he is awarded the expectation incentive in states of the world where the payoff from the centre player contribution is low.

The literature on expectations elicitations is not conclusive on the issue of in-

[14] The literature in economics has recently started analysing the strategic implications of expectation formation when interacting partners are guilt averse. The strategy that manipulates expectation to produce desired outcomes is referred to as "guilt induction" [Cardella, 2012].

[15] This requires (a) the player to be pivotal in determining the average of c_i and (2) that the average value of the expectation has been played by at least some players, which has to be true if the average is 0 and 3, but it is not necessarily the case if the average is 1 or 2.

centives. Delavande et al. [2011] summarise a number of studies in development economics which elicit expectations without using monetary incentives. Gachter and Renner [2010] find that incentives reduce the dispersion of beliefs but do not change the central tendency of the distribution. In our study dispersion is not a concern as expectations can take only 4 values. Schlag et al. [2014] provide a recent review of the various methods to incentivise beliefs and the respective strengths and weaknesses.

2.3 Treatments

We have four treatments. In the baseline treatment T0 all players receive a neutral message and $\bar{\alpha}$ is not disclosed. In the first treatment T1*neutral* we disclose the true $\bar{\alpha}$ to participants, while still distributing a neutral message to each participant. In the last two treatments, we use the messages to shock expectations. In T1*positive* four players are given the positive priming message in order to produce an *upward* shock to their beliefs α_i, and four players are given neutral message number 2. In T1*negative* four players are given the negative priming message in order to produce a *downward* shock to α_i, and four players are given neutral message number 2. Half of the sessions of each treatment are played with $r = 3/4$ and half of the sessions are played with $r = 4/5$. Table 1 summarises.

Table 1: Summary of Treatments

	T0	**T1*neutral***	**T1*positive***	**T1*negative***
Disclose $\bar{\alpha}^z$		✓	✓	✓
Message 1	neutral 1	neutral 1	positive	negative
Message 2	neutral 2	neutral 2	neutral 2	neutral 2

Throughout the analysis we will repeatedly perform comparisons between individuals who have been randomly assigned to receive message "neutral 2" across treatments. Up to the point where expectations are elicited, these individuals are exposed to the same protocol irrespective of treatment. They have read the same message. They are equally uncertain about the message that the other four players have received. They do not anticipate that, in T1 sessions, the average of the expectations will be disclosed. Experimental manipulation is limited to the phase where $\bar{\alpha}$ is disclosed.

3 Predictions

We focus on the "centre contribution" decisions c_i.

3.1 Play in T0

The experimental literature has repeatedly found that conditional cooperation is the modal strategy in public good games played with the strategy method by homogenous groups [Chaudhuri, 2011]. A conditional cooperator is somebody whose contribution correlates with the average contribution of the group, sometimes with a small self-serving bias. We define profiles that are strictly increasing in the average of the spokes as corresponding to "strict conditional cooperation". $c_i = (0, 1, 2, 3)$ is the only possible strictly increasing profile in our game. Strategies that are weakly increasing in the average contribution of the spokes and are not flat nor strictly increase, for example $c_i = (0, 0, 1, 2)$ or $c_i = (0, 3, 3, 3)$, are referred to as "weak conditional cooperation". Under this definition, a weak conditional cooperator in the centre of the star can be somebody who contributes (weakly) more than the spoke average in every decision, somebody who always contributes (weakly) less than the spoke average in every decision, or neither.

Strict conditional cooperation can be the result of an independent social preference, or, in standard public good games, may derive from an underlying preferences for equality of payoffs or for reciprocity. In our game however, the centre of the star may have a number of reasons to contribute above the level of strict conditional cooperation.

First, contributions by the centre of the star *reach* more players and have a much higher effect on aggregate payoff than contributions by the spokes. For same cost in individual payoff terms, contributions by the centre of star generate an effect on the payoff of the other players that is seven times larger than that generated by the contributions of a spoke. Such efficiency considerations may justify a profile that has a higher intercept than $c_i = (0, 1, 2, 3)$, a steeper slope, or both. For example, motivated by his high efficiency, the centre of star may decide to contribute proportionally more than what the spokes contribute. This would result in a profile with a steeper slope. Alternatively, he may decide to exceed conditional cooperation by a fixed absolute amount, for example, the average of the spokes plus one. This would raise the intercept of the profile.

Second, when the average contribution of the spokes is at least one, higher contributions by the centre of the star unambiguously reduce inequality in payoff among players. When the spokes are contributing 0 on average, on the other hand, positive contributions by the centre of the star worsen inequality. Inequality averse players dislike payoff differences of both types [Fehr and Schmidt, 1999] and, for sufficient levels of aversion, would choose the profile $c_i = (0, 3, 3, 3)$.

Third, other players may expect the centre of the star to contribute a higher amount than everybody else, based on the considerations of efficiency and equality that have been presented above. This can create a certain "social pressure" on the central player, which is captured by the model of guilt aversion which we present below. The exact profile that follows in this case depends on the shape of the profile expected by the group and hence cannot be determined a priori.

3.2 Treatment effects

We hypothesise that farmers are guilt averse and that this is an important determinant of the behaviour of the farmer at the centre of the star network. The model of guilt aversion makes a number of specific predictions on how individuals will respond to our treatments. In this subsection, we present the predictions. In the next subsection, we will discuss how we use the experimental data to perform the related statistical tests.

Guilt averse players dislike to "let other players down". More precisely, they dislike to play strategies which determine a lower payoff for other players than what these players expect to get. In our game for example, farmers may expect the centre of the star to contribute generously to the public good. As a consequence, they may expect to earn a high payoff even when they are assigned to the spoke position. In this scenario, a guilt averse centre of the star will feel he is letting the other players down if his contribution does not match the high expectations of these players.

Crucially, in order to quantify the extent to which his actions "let other players down", a guilt averse player has to form an expectation about the payoff other players expect to get. Conditional on a value of s_i, the payoff of a spoke is entirely determined by the contribution of the centre of the star. We let β_i be player i's belief about what contribution, on average, other players expect him to make if he is assigned to the centre position: $\beta_i^z = E_i\left(\bar{\alpha}^z\right)$. In the language of psychological games, β_i is a "second-order belief": a belief about the beliefs of other players.

A guilt averse player at centre of the star maximises the following utility function:

$$u_i(c_i^z, \beta_i^z|z) = \pi_i(c_i^z|z) - g \max\left(\bar{\pi}_j(\beta_i^z|z) - \bar{\pi}_j\left(c_i^z|z\right), 0\right) \tag{2}$$

The first element in utility function 2 reflects the usual concern for monetary payoffs. The second element is a utility penalty for contribution choices that determine an average payoff for the spoke players that is $\bar{\pi}_j(\beta_i^z|z) - \bar{\pi}_j(c_i^z|z)$ units lower than what the centre player thinks the spoke players expect. For simplicity, we assume g is linear and β_i^z is a point belief. Furthermore, the literature has not yet tackled the issue of how a guilt averse individual reacts to a distribution of expectations among a set players. Our working assumption is that he will focus on the average value of the expectation distribution. We flag this as an area for further research.

Suppose $c_i^z < \beta_i^z$. In this case, player i thinks that the other players are earning a lower payoff than the payoff they expect to get- he feels *guilty* about this. Contributing one more note decreases guilt by gr50, while decreasing the monetary payoff by (1-r)50. When $g > \frac{1-r}{r}$, the reduction in guilt outweighs the loss of monetary payoff and the centre of the star finds it optimal to contribute what he thinks other players expect him to contribute: $c_i^{z*} = \beta_i^z$.[16]

In treatments T1*neutral*, T1*positive*, and T1*negative*, we disclose the true value of $\bar{\alpha}^z$, for each value of z. Thus, when players take the "centre contribution" decisions c_i^z, the belief β_i^z has been updated to reflect the true $\bar{\alpha}^z$. In these treatments, for sufficiently guilt averse players with $g > \frac{1-r}{r}$, $c_i^{z*} = \bar{\alpha}^z$. When players indeed set $c_i^z = \bar{\alpha}^z$, we say that there is a match between contributions and group expectations.

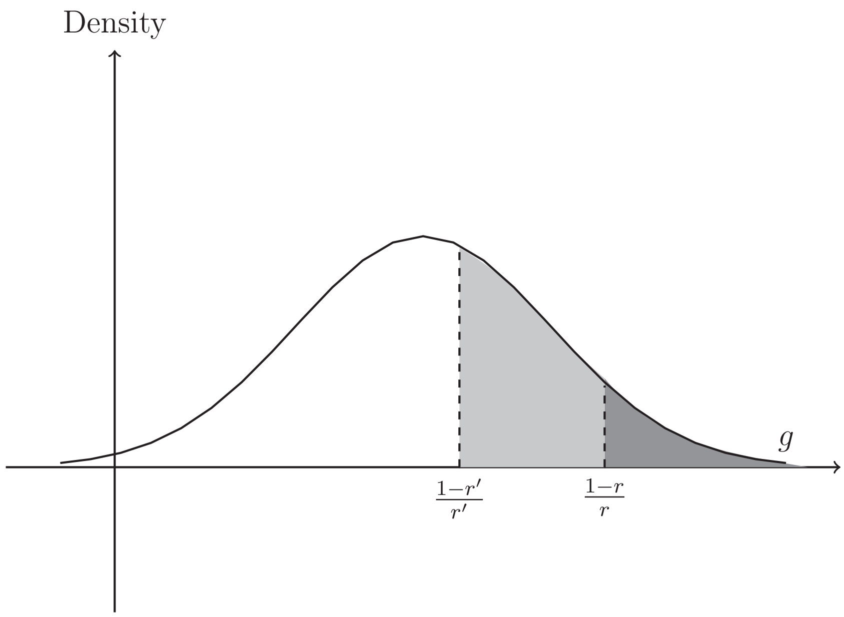
Random variation of r across sessions allows us to formulate the first testable prediction of the model of guilt aversion. The parameter r determines the monetary cost of contributing one more note to the public good. The higher r, the lower the cost of increasing contributions, and of reducing guilt when positive contributions are expected. Given a non degenerate distribution of g in the population, as r gets higher more people will match their contribution to the disclosed $\bar{\alpha}^z$. Figure 3 illustrates. In the figure, we assume g is normally distributed in the population. Integration from $\frac{1-r}{r}$ to infinity gives the fraction of players who set $c_i^{z*} = \bar{\alpha}^z$ when

[16]Contributions above β_i^z, on the other hand, are always dominated by contributions matching β_i^z, as they entail an additional reduction in monetary payoff and no further reduction in guilt.

the rate of return is r. This is represented by the dark grey area in the figure. Suppose now we switch to a different rate of return $r' > r$. Notice $\frac{1-r}{r} > \frac{1-r'}{r'}$. The fraction of players who set $c_i^{z*} = \bar{\alpha}^z$ is now given by the sum of the light and dark grey areas and is larger. This shows that matches between contributions and group expectations will be more frequent in sessions randomly assigned to a high level of r:

Prediction 1. *Players who receive message neutral 2 in a T1 session assigned to $r = 4/5$ are more likely to choose contributions c_i^z that are equal to $\bar{\alpha}^z$ than players who receive the same message in a T1 session assigned to $r = 3/5$.*

Figure 3: An increase in the rate of return to public good contributions



In treatments T1*positive* and T1*negative* we introduce random shocks to the level of group expectations. If the positive message in T1*positive* succeeds in raising α_i for the four players who receive the priming message, $\bar{\alpha}$ will be higher in T1*positive* sessions than in T1*neutral* sessions. Players who receive message neutral 2 now have to contribute higher amounts to minimise their guilt. As long as $g > \frac{1-r}{r}$ for at least some players who receive message neutral 2, contributions will be higher in T1*positive* than in T1*neutral*. A symmetric argument applies to T1*negative*. We hence make the following prediction:

Prediction 2. *The contributions c_i^z of players who receive message neutral 2 in treatment T1*positive *and T1*negative *are, respectively, significantly higher and lower than those of players who receive message neutral 2 in treatment T1*neutral.

This increase (decrease) will be proportional to the difference between the average $\bar{\alpha}$ disclosed in T1*neutral* sessions and the average $\bar{\alpha}$ disclosed in T1*positive* (T1*negative*) sessions. This implies that if our experimental manipulation fails to affect average expectations no treatment effects will be found.

Finally, under the assumption that $g > \frac{1-r}{r}$ for at least some players, we can learn whether individuals hold correct β_i^z expectations by comparing decisions in T1*neutral* and in T0. If baseline β_i^z expectations are frequently inaccurate, guilt averse individuals in T0 will often fail to match their contributions to the true $\bar{\alpha}$. Disclosure of $\bar{\alpha}$ in T1*neutral* will then increase the frequency of $c_i^z = \bar{\alpha}^z$ matches.[17] Some inaccuracy in expectations is likely, and we hence predict that the frequency of matches will be higher in T1*neutral*.

If match frequency increases, the effect on average contributions is ambiguous and depends on whether guilt averse players with inaccurate priors revise these priors upwards or downwards, after disclosure of $\bar{\alpha}^z$.[18]

Prediction 3. *Players in T1*neutral *are more likely to choose contributions c_i^z that are equal to $\bar{\alpha}^z$ than players in T0.*

3.3 Analysis

We analyse contribution and expectation profiles in two ways. First, we study the average intercept and slope of contribution and expectation profiles with regression

[17]This argument rests on the assumption that farmers are certain about the value of $\bar{\alpha}^z$- β_i^z is a point belief and not a distribution- and that g is linear. If farmers are uncertain about the beliefs of their peers and g is concave, disclosure of $\bar{\alpha}$ can increase contributions even when the mean of the distribution of β^z is correct.

[18]A simple example illustrates. Suppose there are three types of players, each occurring in the population with equal frequency: guilt indifferent and selfish, guilt averse with accurate priors $\beta_i = \bar{\alpha}$, guilt averse with inaccurate priors $\beta_i = p$. In T0, the average level of contributions spoke average is z will be: $(\frac{1}{3} * 0) + (\frac{1}{3} * \bar{\alpha^z}) + (\frac{1}{3} * p^z)$. In T1*neutral*, players with inaccurate priors revise these and now contribute $\bar{\alpha}^z$. The new average will be: $(\frac{1}{3} * 0) + (\frac{2}{3} * \bar{\alpha^z})$. The difference in average contributions across treatments is given by$\frac{1}{3}(\bar{\alpha^z} - p^z)$. Contributions increases in T1*neutral* only in cases where guilt averse players with inaccurate priors underestimate the expectations of others.

analysis. We pool the four decisions or expectations of each player and create a small panel with four observation per player. Suppose a profile takes the following linear form:

$$x^*_{iz} = \kappa + \beta_1 z + u_{iz} \tag{3}$$

where x^*_{iz} can be either the contribution decision c^z_i, or the expectation α^z_i. The intercept κ measures the level of x^* when spoke average contribution z is 0, while β_1 captures the increase in x^* when z increases by one unit. Under strict conditional cooperation $\kappa = 0$ and $\beta_1 = 1$. Other values of κ and β_1 are also possible. However, participants are endowed with only three notes in the game. Hence, what we observe is:

$$x_{iz} = min\,(max(0, x^*_{iz}), 3) \tag{4}$$

In our data corner solutions at both 0 and 3 occur frequently. We hence estimate values of κ and β_1 using a tobit model with a lower limit at 0 and an upper limit at 3. We then provide two-sided Wald tests of the hypotheses $\kappa = 0$ and $\beta_1 = 1$ and study the direction of any deviation. To separately analyse the intercept and slopes for the T0 treatment, we introduce a dummy for being in a T1 treatment and an interaction term capturing any additional effect of z in T1 sessions:

$$x^*_{iz} = \kappa + \beta_1 z + T1 + \beta_2(T1 * z) + u_{iz} \tag{5}$$

In model 5, κ and β_1 identify the intercept and slope of profiles in T0 sessions.

A potential problem of the estimation strategy above is that it assumes variable x^*_{iz} is continuous. We can show the general point that "centre-contribution" decisions increase with the average investment of the spokes using other estimation models that do not depend on this assumption. Ordered logit, for example, requires only that data is available in ordinal form. This is satisfied in our case. The ordered logit estimate of β_1 can be given the same interpretation as above: it captures the change in x^*_{iz} that results from an increase in average spoke contribution z of 1 unit. This is the effect we are interested in and thus it is the effect we report. One drawback of ordered logit is that we cannot easily estimate and perform statistical analysis on the intercept of the profile.

Second, we categorise each individual profile in terms of its archetypal shape and report the relative frequency of each shape. The archetypal shapes we consider are:

1. **Strictly increasing**: $c_i^{z+1} > c_i^z$, for $z \in \{0, 1, 2\}$
2. **Flat**: $c_i^{z+1} = c_i^z$, for $z \in \{0, 1, 2\}$
3. **Weakly increasing**: $c_i^{z+1} \geq c_i^z$, for $z \in \{0, 1, 2\}$ and the profile is not strictly increasing and not flat
4. **Decreasing**: $c_i^{z+1} \leq c_i^z$, for $z \in \{0, 1, 2\}$ and profile is not flat
5. **Peak at 1**: $c_i^1 > c_i^0$, and $c_i^{z+1} < c_i^z$ for $z \in \{1, 2\}$
6. **Peak at 2**: $c_i^{z+1} > c_i^z$ for $z \in \{0, 1\}$ and $c_i^3 < c_i^2$, and

The only strictly increasing profile possible in our game is $c_i = (0, 1, 2, 3)$. As explained before, we define this as "strict conditional cooperation". We define weakly increasing profiles as "weak conditional cooperation".

To investigate prediction 1 we estimate the following linear probability model:

$$match\,(c_i^z = \bar{\alpha^z})_{iz} = \delta + High\ Rate\ of\ Return + e_{iz} \tag{6}$$

$match\,(c_i^z = \bar{\alpha^z})_{iz}$ is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha^z}$, that is, if the contribution decision matches the group expectation. Variable $High\ Rate\ of\ Return$ is a second dummy which indicates whether the session-level rate of return to investing in the public good is $\frac{4}{5}$. We estimate model 6 using OLS over the sample of individuals who receive message neutral 2 in T1 treatments. We include dummy controls for the values of average spoke contribution z and for the treatment in which the decision is taken.

A positive and significant coefficient on $High\ Rate\ of\ Return$ would confirm prediction 1. The model of guilt aversion we have presented suggests that this effect is the result of players' desire to align their contribution profiles to the average group expectations which we disclose. However, a higher frequency of matches between c_i^z and $\bar{\alpha^z}$ can also come about in two other ways. First, when players align contributions c_i^z to first-order expectation α_i^z more frequently, and the distribution of α_i^z has significant weight on the mean.[19] Individuals in the centre of the star may have different reasons to conform to the decisions they expect others to take. For example, they could be motivated by a wish to abide to respected social norms. We will check whether this effect is at work using a regression model of this form:

$$match\,(c_i^z = \alpha_i^z)_{iz} = \delta + High\ Rate\ of\ Return + e_{iz} \tag{7}$$

Second, when r is high, players may hold more realistic forecasts about what the other players will do. We will not be able to offer an independent test of this second mechanism. However, there are no real theoretical reasons suggesting that expectations will be significantly more precise for a higher value of r. Furthermore, our treatments T1*positive* and T1*negative* introduce exogenous, undisclosed shocks to the value of $\bar{\alpha^z}$. Treatment effects generated by this manipulation can be explained by guilt aversion, but not by changes in the precision of expectations.[20]

In some specifications of regression model 6, we also include controls for factors that may moderate the effect of group expectations on behaviour and we interact these with the treatment dummy $High\ Rate\ of\ Return$. We are particularly interested in two variables: individual and average degree in the real-life network that links the participants of the experiment and self-reported oneness.

We hypothesise that farmers will respond more readily to group expectations when they are linked to many of the group members, and when the average number of links within the group is high. For this purposes, we rely on dyadic data which we collect at the end of each session. This data describes the bilateral relationship of each player with the other seven players. We consider that a link exists between i and j when they have spoken at least once in the past 30 days. The literature in behavioural economics has argued that individuals have stronger other-regarding concerns for peers who are close in the network [Goeree et al., 2010, Leider et al., 2009, Ligon and Schechter, 2012]. Social psychologists have also put forward the

[19]If this was not the case, such alignment could actually determine a decrease in the proportion of matches between c_i^z and $\bar{\alpha^z}$. Suppose for example that half of the players set $\alpha_i^z = 0$ and the other half sets $\alpha_i^z = 2$. In this case, $\bar{\alpha^z} = 1$. If everybody aligns c_i^z to α_i^z, the number of matches between c_i^z and $\bar{\alpha^z}$ will be zero. On the other hand, suppose all players set $\alpha_i^z = 1$. Again, $\bar{\alpha^z} = 1$. Aligning c_i^z to α_i^z will now bring the fraction of the matches between c_i^z and $\bar{\alpha^z}$ to 100 percent

[20]By design, the expectations α_i^z of individuals who receive message neutral 2 are not affected by this treatment. The model of guilt aversion, on the other hand, generates precise, testable prediction on how individuals will respond to changes in $\bar{\alpha^z}$. See below.

hypothesis that guilt is stronger for close ties [Baumeister et al., 1994]. Both of these strand of work make predictions at the dyadic level. In our experiment, on the other hand, the player is confronted with the average expectation of a set of players. Here it is unclear it is individual or the session-level network statistics that make group expectations more salient for decisions makers. We test for both possibilities.

We also hypothesise that a feeling of connection with the other farmers in the group would make a player particularly responsive to group expectations. This feeling is embodied in the construct of "oneness" developed in the literature in social psychology. The feeling of oneness is defined as "a sense of shared, merged, or interconnected personal identity" [Cialdini et al., 1997]. Recent experimental evidence in economics points to the importance of oneness as predictor of behaviour in strategic environments [Tufano et al., 2012]. We obtain a self-reported measure of oneness by including in the end-questionnaire the same visual survey items developed by Aron et al. [1992] and deployed in the subsequent literature in social psychology. We report this items in figure 7 in the appendix.

To test prediction 2, we estimate the following variations of model 5 over the sample of individuals in sessions T1*neutral*, T1*positive* and T1*negative* that have received message neutral 2:

$$x^*_{iz} = \kappa + T1positive + T1negative + u_{iz} \tag{8}$$

$$x^*_{iz} = \kappa + \beta_1 z + T1positive + T1negative + \beta_3(T1positive * z) + \beta_4(T1negative * z) + u_{iz} \tag{9}$$

Now the excluded category is the T1*neutral* treatment. Our main prediction is that the coefficient on the T1*positive* dummy in model 8 is positive and significant, and that the coefficient on the the T1*negative* dummy is negative and significant. These coefficients measure differences in average contributions across treatments, pooling over all four decisions. In model 9, we test separately whether effects identified in model 8 are produced by a shift in the intercept or a change in the slope of the contribution profiles.

Finally, to investigate prediction 3 we restrict attention to the the sample of individuals who have received message neutral 2 in T1*neutral* and T0 and estimate the following regression models:

$$match\,(c_i^z = \bar{\alpha^z})_{iz} = \delta + T1neutral + e_{iz} \tag{10}$$

$$x^*_{iz} = \kappa + T1neutral + u_{iz} \tag{11}$$

$$x^*_{iz} = \kappa + \beta_1 z + T1neutral + \beta_2(T1neutral * z) + u_{iz} \tag{12}$$

We will estimate regression model 10 using OLS and models 11 and 12 using tobit. Model 10 will test whether disclosure of group expectations makes matches between contributions and group expectations more frequent in T1*neutral* compared to T0. Models 11 and 12 will explore whether the level of contributions is affected by disclosure of group expectations, and, if so, whether this happens through a change of the slope or of the intercept of the contribution profile.

To account for within-session dependence, we correct standard errors for clustering at the session level in all models presented in this section. With 98 sessions, we have a sufficient number of clusters to apply this correction.

4 Data

We run our field experiment in 4 "talukas" (sub-districts) of the Indian state of Maharashtra in January and February 2014. These are the same 4 "talukas" where, in September and October 2013, we ran the link formation experiment which is presented in a previous chapter of this dissertation.

As in the previous chapter, study participants are selected through door-to-door random sampling. Male adult farmers who are encountered in this exercise are invited to join the game. We run only one session per selected village.

We run 98 sessions with 765 subjects. We have 24 sessions of T0 and T1*negative* and 25 sessions of T1*neutral* and T1*positive*. In 11 sessions we played the game with 7 participants and in 4 sessions we played the game with 3 participants. This was caused by two factors: (i) in 1 case were we were not able to find 8 available farmers with door-to-door sampling and we started the session with 7 farmers, (ii) in 18 cases farmers left after the beginning of the game.[21] As shown later in the balance analysis, the number of individuals per session is not correlated with treatment. Table 2 summarises the number of sessions and individual observations we have for each treatment.

Table 2: Number of observations by treatment

Treatment	**Sessions**	**Players**
T0	24	187
T1*neutral*	25	194
T1*positive*	25	195
T1*negative*	24	189
Total	98	765

At the end of the game, participants compile a short questionnaire. We hence have a small set of covariates.[22] Average age is 37 years. 76 percent of participant do not belong to a scheduled caste, tribe or an other backward caste (OBC), 32 percent of them have completed high school. We also find that average total land holdings are about 4 hectares and average land cultivated is 3.1 hectares. On average, farmers report sharing information about agriculture on a regular basis with 7 other farmers. Overall, this sample has very similar average characteristics to the sample that played the link formation game.

The farmers who take part in the experiment know each other well. In the end-questionnaire we ask farmer i on how many days of the previous 30 days he has had a conversation with each of the other players. The density of the within-session networks we record is very high: 61 percent of farmers have spoken with all the other farmers and, on average, a farmer has spoken with 6 of the other 7 farmers.

[21] In most cases, famers who left did so early on in the game, before actual decisions were made. When the game was played with 7 or 6 participants none of the rules were changed. The main difference is that the contribution of the centre player now reaches 1 or 2 individuals less.

[22] When participants fail to answer a question or report an illegible script, we code a missing value. This explains the changing number of observations in table 3.

Table 3: Summary statistics: Individual Covariates

Variable	Mean	Std. Dev.	Min.	Max.	N
Age	36.942	10.57	19	75	760
Non backward caste	0.765	0.424	0	1	745
Completed High School	0.326	0.469	0	1	748
Land Owned	4.115	5.175	0	68	761
Land Cultivated	3.158	4.49	0	68	757
Information network size[23]	6.972	4.857	0	20	744
Oneness	5.995	1.547	1	7	747

Conditional on speaking, farmers have on average spoken with the other farmers in the session on 7.5 of the previous 30 days.

A second piece of descriptive evidence confirms the tight nature of the social bond between participants: self reported oneness in our sample is very high. More than 70 percent of players who answer the question choose the highest possible level of oneness. Figure 8 in the appendix illustrates.

Table 4: Summary statistics: Session Networks

Variable	Mean	Std. Dev.	Min.	Max.	N
Farmers with whom i has spoken	6.04	1.68	0	7	747
Average number of days spoken	7.5	6.62	1	30	725

Note. The first variable reports the number of farmers with whom farmer i has spoken on a least 1 day in the last 30 days. The second variable reports the average number of days spoken with the other farmers, conditional on speaking on a strictly positive number of days.

We check participants' understanding of the game by means of a initial battery of 9 questions. These cover understanding of the network map, ability to calculate payoffs, awareness of the incentives created by the payoff rule, and understanding of the strategy method. Figure 9 in the appendix reports the cumulative distribution of mistakes in these questions. About 48 percent of individuals make 2 mistakes or less in the 9 questions. Following the understanding test, enumerators reveal the right answers to the questions and give further instructions if necessary. Hence the understanding level reported in figure 9 is a lower bound of the actual understanding of players at the time of play.

In tables 10 to 12 in the appendix, we present some regressions that test for covariate balance across treatments. We cannot find any statistically significant difference in average characteristics across treatments, in the number of mistakes made in the understanding questions, nor in the number of individuals who choose to leave before the end of the game.

5 Results

We organise the discussion around five results.

Result 1. *The contribution profiles of the centre of the star are consistent with conditional cooperation. The spokes contribute on average half of the endowment. 49.7 percent of the potential gains from cooperation are realised.*

Regression analysis shows that high understanding players choose contributions profiles consistent with strict conditional cooperation. In the first four columns of table 5 we report tobit estimates of the coefficients in model 5. When we run the regression over the whole sample of decision makers and without controls, the point estimate of coefficient β_1 is 0.73 and highly significant. A Wald test indicates that this coefficient is significantly lower than one, while the coefficient on the constant κ is significantly higher than 0 at the 10 percent level. Thus, on average, players choose contribution profiles with a higher intercept and a flatter slope than those implied by "strict conditional cooperation". However, when we restrict the analysis to high understanding players, the intercept becomes statistically indistinguishable from 0, and the point estimate of β_1 is very close to 1. A Wald test cannot reject the null hypothesis that this coefficient is equal to 1. High understanding players, on average, play "strict conditional cooperation". This is evident when, in figure 4a, we plot the predicted profiles that are implied by the regression estimates.

In the tobit model the independent variable z is constrained to have the same effect on the likelihood that the dependent variable is at a corner solution and on the value of the dependent variable when this is away from the corner. We provide qualitative evidence to support this assumption by running a probit regression to predict the probability of choosing a contribution value above 0, and the probability of choosing a contribution value of 3. Table 16 in the appendix shows the results.

In both cases, the coefficient on spoke average contribution z has the same direction as in the tobit model, and has a magnitude that is lower, but roughly comparable.

The next four columns of table 5 report ordered logit estimates. These show that the significance of the coefficient β_1 is robust to the introduction of this alternative estimation strategy. The magnitude is also similar to that reported for the tobit model. In all four specifications, the point point estimate of β_1 is statistically indistinguishable from 1.

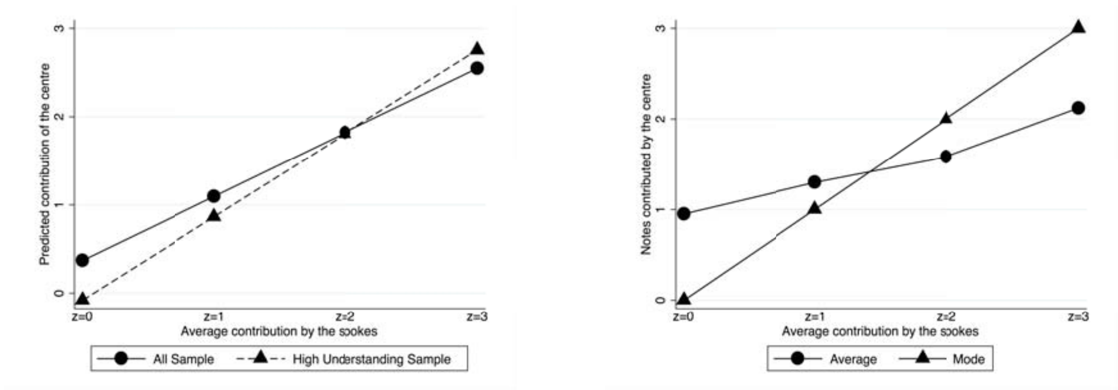
Table 5: Regression: contributions of the centre player

	Tobit				Ordinal Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a								
Spoke average	.726	.773	.945	1.003	.828	.877	1.134	1.180
	(.108)***	(.106)***	(.101)***	(.104)***	(.123)***	(.120)***	(.119)***	(.120)***
T1	.161	.205	.052	.132	.229	.291	.190	.257
	(.247)	(.261)	(.323)	(.336)	(.261)	(.271)	(.342)	(.352)
T1*Spoke average	-.103	-.150	-.144	-.225	-.154	-.207	-.224	-.290
	(.119)	(.118)	(.116)	(.120)*	(.127)	(.125)*	(.125)*	(.126)**
Const.	.369	.141	-.080	-.433				
	(.220)*	(.354)	(.297)	(.492)				
Panel b								
H0 $\beta = 1$, H1 $\beta \neq 1$	6.38	4.54	0.30	0.00	1.98	1.05	1.28	2.24
	(.012)**	(.033)**	(.585)	(.976)	(.16)	(.306)	(.258)	(.135)
Obs.	3060	2732	1496	1344	3060	2732	1496	1344
Cluster N	98	98	98	98	98	98	98	98
Pseudo R^2	.046	.047	.08	.081	.058	.061	.102	.104
Log-likelihood	-4581.009	-4082.093	-2144.804	-1925.252	-3985.161	-3550.656	-1847.164	-1657.385
Controls		✔		✔		✔		✔
High Understanding			✔	✔			✔	✔

The dependent variable is the number of notes contributed to the public good by player i for "centre contribution" decision z. The first four columns present a tobit regression, with an upper limit of 3 and a lower limit of 0. The last four columns present an ordinal logit regression. Columns 3,4,7,8 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2, 4, 6, 8 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level. Panel b reports the F statistics (and p value in parenthesis) for a one-sided Wald test on estimated coefficient $\hat{\beta}$.

Graphical analysis of average and modal values of contribution decisions c_i^z confirms that these closely match the average contribution of the spoke players. Figure 4b illustrates.

Figure 4: Contribution profiles of the centre of the star



(a) Predicted profiles

(b) Mode and average in the data

The profile $c_i = (0, 1, 2, 3)$ is the most frequently chosen by farmers in the game. About 20 percent of them choose this profile and can hence be classified as "strict conditional cooperators". Tables 13 and 14 in the appendix report this data. Farmers also choose a variety of strategies that are weakly increasing in the average contribution of the spokes. These add up to 22 percent of all profiles. If we restrict the analysis to high understanding players, weakly increasing profiles account for about 38 percent of all profiles. The majority of high understanding players (57 percent) thus chooses strategies that increase (strictly or weakly) with the average of the spokes. Figure 5 illustrates.

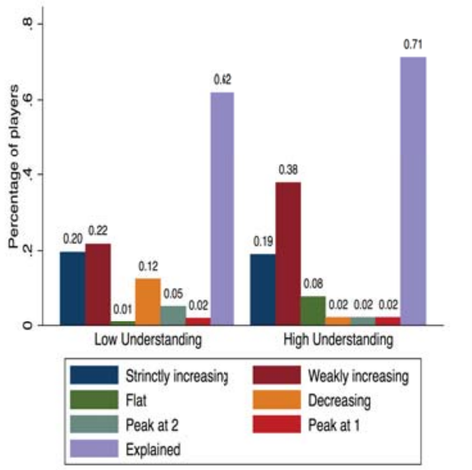
The three most common weakly increasing strategies are: $(0, 0, 1, 3)$, $(0, 0, 1, 2)$, and $(0, 0, 2, 2)$. These are all profiles in which the centre of star contributes weakly less than the average contribution of the spokes in every decision.

The remaining profiles show a large degree of heterogeneity. A small group of players do not condition their contributions on the average of the spokes. This group is composed both of players who never contribute anything (4.4 percent of high understanding players) and players who always contribute the full amount (3.3 percent of high understanding players). A second group chooses profiles where contributions weakly or strictly decrease with the average contribution of the spokes. However, this group is mostly composed of low understanding players. A third group chooses profiles that peak when spoke average contribution is 1 or 2.[24] Finally, about 34 percent of low understanding players and 26 percent of high understanding players choose profiles that are not consistent with the archetypal candidates we have

[24]This type of profile was documented also in the study of Fischbacher et al. [2001].

listed.

Figure 5: Archetypal contribution profiles, by understanding



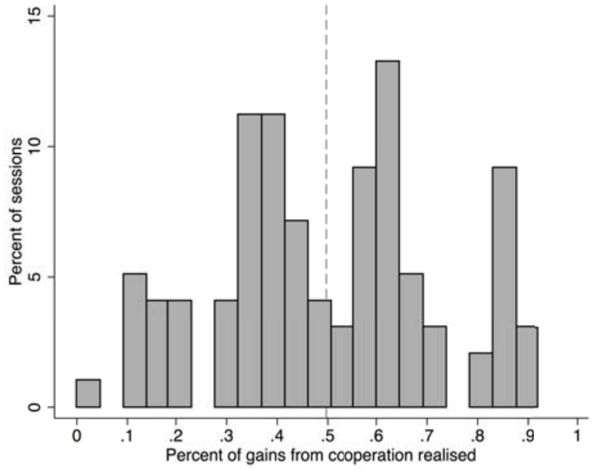
We have focused so far on the profile of four decisions taken by the centre of the star. Only one of these decisions is implemented at the end of the game. The average contribution of the spokes determines which of the decisions is implemented. Spokes contribute on average 1.496 notes. After rounding, 51 percent of sessions have a spoke average of 1 and 47 percent a spoke average of 2. Given this, the centre player on average contributes 1.49 notes. Figure 10 in the appendix illustrates.

The sum of group payoffs is maximised when every player contributes the maximum number of notes to the public good. In our data, the combination of conditional cooperation and a relatively low average contribution level of the spokes determine that only about 50 percent of the potential gains from cooperation are realised.[25] This is shown in figure 6.

We now turn to the analysis of expectation profiles α_i. Our main result is the following:

[25]Let $\Pi(3, r)$ be the sum of payoffs that would accrue to each player if every player contributes 3 notes to the public good when the return to investing in the public good is r. Define $\Pi(0)$ as the sum of payoffs when every player contributes 0 notes to the public good. $\Pi(3, r) - \Pi(0)$ represents the increase in aggregate payoff that is achieved when players make the maximum contributions to the public good. These are the potential "gains from cooperation". Let Π_s be the sum of individual payoffs in session s. $\frac{\Pi_s - \Pi(0)}{\Pi(3,r) - \Pi(0)}$ indicates the fraction of the potential gains from cooperation that is realised in session s.

Figure 6: Aggregate Efficiency



See note 25 for a mathematical definition of "gains from cooperation".

Result 2. *Players expect conditional cooperation from the centre of the star*

Our strongest piece of evidence is given by tobit estimation of model 5 with expectations α_i^z as the dependent variable. Coefficient β_1 now measures the extent to which players *expect* others to increase their centre of the star contributions when the average spoke contribution increases. Table 6 reports the coefficient estimates. The average expectations profiles reported for the unrestricted sample have a positve value of κ, significantly higher than 0, and a positive value of β_1. When we restrict the sample to high understanding players in column 3, κ is not significantly different from 0 and β_1 is not significantly different from 1. These results are similar to those for contribution profiles reported in table 5. High understanding farmers in our sample expect strict conditional cooperation.

Table 6: Regression: expectations about the contribution of the centre player

	Tobit				Ordinal Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a								
Spoke average	.670	.679	.946	1.039	.688	.687	1.003	1.056
	(.089)***	(.095)***	(.084)***	(.108)***	(.091)***	(.096)***	(.094)***	(.114)***
T1	-.220	-.175	-.342	-.104	-.230	-.175	-.351	-.124
	(.215)	(.238)	(.311)	(.365)	(.209)	(.226)	(.298)	(.332)
T1*Spoke average	.088	.089	.108	.00008	.093	.090	.127	.025
	(.106)	(.112)	(.107)	(.133)	(.101)	(.106)	(.103)	(.122)
Const.	.427	-.179	-.113	-1.145				
	(.175)**	(.328)	(.269)	(.468)**				
Panel b								
H0 $\beta = 1$, H1 $\beta \neq 1$	13.72	11.38	0.41	0.13	11.78	10.71	0.00	0.24
	(.000)***	(.001)***	(.524)	(.719)	(.001)***	(.001)***	(.971)	(.626)
Obs.	3060	2732	1496	1344	3060	2732	1496	1344
Cluster N	98	98	98	98	98	98	98	98
Pseudo-R^2	.053	.055	.101	.1	.066	.067	.126	.123
Log-likelihood	-4534.488	-4038.437	-2084.425	-1873.702	-3955.106	-3527.313	-1799.159	-1622.836
Controls		✔		✔		✔		✔
High Understanding			✔	✔			✔	✔

The dependent variable is expectation α_i^z. The first four columns present a tobit regression, with an upper limit of 3 and a lower limit of 0. The last four columns present an ordinal logit regression. Columns 3,4,7,8 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2, 4, 6, 8 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level. Panel b reports the F statistics (and p value in parenthesis) for a one-sided Wald test on estimated coefficient $\hat{\beta}$.

The most frequent expectation profile is the strictly increasing profile $\alpha_i = (0, 1, 2, 3)$. As before however, the combined category of weakly increasing profiles occurs more frequently than the strictly increasing profile. The most common weakly increasing profiles are: $(0, 0, 1, 3)$, $(0, 0, 1, 2)$, and $(0, 1, 2, 2)$. Again, these are all profiles where the centre of star contributes weakly less than the spokes for every decision. These results are reported in figure 11 and table 15.

Expectations are on average correct, as shown in figure 12 and as the similarity of the estimated regression coefficients κ and β_1 in tables 5 and 6 indicates. However, expectations are not particularly precise. In figure 13 we compute, for each decision z, the probability that player i's expectation α_i^z is equal to the average value of c_i^z among the other seven players in the session. In other words, we calculate the fraction of times in which farmers correctly guess the behaviour of the other farmers in the group. We calculate a confidence interval around this probability and test whether it lies above the probability of having an accurate expectation when this expectation is randomly chosen.[26] For α_i^1, α_i^2 and α_i^3 farmers' predictions are correct significantly more often than random predictions. However, for α_i^1 and α_i^3 , the confidence interval is actually very close to including the value under random prediction. Furthermore, even for decision c_i^2, which farmers are best at predicting, mistaken predictions are more common than correct guesses.

There is a correlation between expectations and strategies, but this is by no means perfect. 60 percent of players who expect strict conditional cooperation from others are strict conditional cooperators themselves, while 13 percent of players who do not expect strict expect conditional cooperation from others choose a profile consistent with strict conditional cooperation. The respective numbers for farmers who choose weakly increasing profiles are 50 and 20 percent. Similarly, 50 percent of players who choose a flat contribution profile also expect others to choose a flat profile, while only 4 percent of players who do not choose a flat profile expect others to choose a flat profile. Figure 14 illustrates. These figures are so high that one may suspect that many players choose the "same" contribution profile that they expect others to play. However, in only 15 percent of cases $c_i^z = \alpha_i^z \; \forall \, z$, as shown in figure 15.

We now move to investigation of the main predictions regarding our treatments. Our result on the first prediction is the following:

Result 3. *In T1 treatments with $r = \frac{3}{5}$, 42 percent of contribution decisions c_i^z match the group expectation $\bar{\alpha}^z$. Matches become more frequent when the rate of return to investing in the public good increases to $r = \frac{4}{5}$. For high understanding players, match frequency significantly increases by 11 percentage points (31 percent).*

This is evidence in support of prediction 2. When we look at the whole sample of players who receive message neutral 2 in T1 treatments, 42 percent of decisions match the group expectation that has been disclosed on the board.[27] The frequency of matches increases by 3 percentage points when the rate of return to investing in the public good is raised from $\frac{3}{5}$ to $\frac{4}{5}$. If we restrict the analysis to high understanding players, 48 percent of decisions match the group expectation. The higher rate of

[26] As there are four possible values of c_i^z, the probability of picking the right value when guessing at random is 0.25.

[27] This is true when we look at the whole sample and when we restrict to high understanding players. See figure 16 in the appendix.

return now generates a significant 11 percentage points increase in the frequency of matches in the regression without controls, and a highly significant 15.6 percentage points increase in the regression with controls. These are large effects: 31 and 58 percent of the baseline frequency, respectively. Furthermore, consistently with our model, the larger part of this effect (77 percent) comes from a reduction in the frequency of decisions where $c_i^z < \bar{\alpha}^z$. Figure 16 in the appendix illustrates.

Table 7: Linear Probability Model: match between contribution c_i^z and group expectations $\bar{\alpha}^z$

	(1)	(2)	(3)	(4)
High rate of return	.028	.043	.110	.156
	(.043)	(.044)	(.058)*	(.059)***
Const.	.376	.376	.352	.268
	(.050)***	(.132)***	(.072)***	(.187)
Obs.	1152	1036	592	532
Cluster N	74	73	66	62
Controls		✔		✔
High Understanding			✔	✔

OLS regression. The dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha}^z$. "High rate of return" is a dummy for whether the session value of r is $\frac{4}{5}$. The sample includes all players who have received message neutral 2 in treatments T1*neutral*, T1*positive*, T1*negative*. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. All regressions include dummies for whether spoke average z is equal to 1, 2, or 3 and for whether treatment is T1*positive* or T1*negative*. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level.

A high rate of return to investments in the public good has no comparable effect on the frequency of matches between contributions c_i^z and individual expectations α_i^z. Table 17 in the appendix reports regression results. Over the whole sample, the frequency of these matches increases by an insignificant 1 percentage point. Restriction to high understanding players does not change this coefficient significantly.

Furthermore, the change in the rate of return to contributions has only a mild effect on the *level* of individual expectations, and has no statistically significant effect on the level of $\bar{\alpha^z}$, nor on the level of contributions. Table 18 in the appendix reports all regression estimates. Thus, while a higher value of r significantly affects the frequency of matches between contributions and group expectations, it does not cause contemporaneous changes in other choice variables.

We investigate a number of other factors that may moderate the effect of group expectations and hence determine the frequency of matches. We focus in particular on individual degree, average session-level degree and on the self-reported feeling of oneness. Table 19 in the appendix report results of regressions where we do not include the interaction between the variable of interest and the treatment dummy. When we restrict the sample to high understanding players, the coefficients on average degree and on oneness are positive but small. The other coefficients are very close to 0. In no specification we are able to find statistically significant effects.

On the other hand, the interaction between a high rate of return and a high level of average session degree is positive, significant and of a large magnitude. Figure 17 plots the predicted treatment effect for different percentiles of the distribution of average degree. At the tenth percentile, the effect is slightly negative. At the ninetieth percentile the effect is close to a 0.3, which corresponds to a thirty percentage point increase in the likelihood of a match. The interaction with individual degree, on the other hand, is not significant. The interaction with oneness has a negative coefficient and is significant at the 10 percent level. Table 20 presents these results.

We now move to prediction 2.

Result 4. *The manipulation of expectations is weak. We cannot offer a test of prediction 2.*

The manipulation of expectations is weak. Table 8 shows regression estimates that illustrate this point. The $\bar{\alpha}^z$ values which we disclose publicly are not significantly higher (lower) in T1*positive* (T1*negative*) sessions compared to T1*neutral* sessions. This is true both if we pool the four values together in a small panel of sessions, or if we analyse each average expectation value separately. We shed some light on how this comes about by comparing the expectations of individuals who received message neutral 1 in T1*neutral*, to the expectations of individuals who received the positive message in T1*positive*, and individuals who received the negative message in T1*negative*. This analysis, reported in tables 21 and 22 in the appendix, shows that the positive message fails to significantly affect expectations, while the negative message reduces them by about half a unit, an effect which we can detect with some statistical precision. The reduction of expectations in T1*negative* is not of a sufficiently large magnitude to modify the group average in a significant way. As average session-level expectations are not affected by the treatment, we cannot offer a convincing test of prediction 2. Such prediction, in fact, rests on the premise that expectations have been experimentally manipulated in the hypothesised direction.

Table 8: Ordered logit regression over session-level average expectations $\bar{\alpha}^z$

	All $\bar{\alpha}^z$	$\bar{\alpha}^0$	$\bar{\alpha}^1$	$\bar{\alpha}^2$	$\bar{\alpha}^3$
	(1)	(2)	(3)	(4)	(5)
T1*positive*	-.366	-.638	.228	-.486	-.356
	(.410)	(.558)	(.608)	(.572)	(.648)
T1*negative*	-.498	-.638	-1.002	-.238	-.184
	(.358)	(.558)	(.706)	(.578)	(.653)
Obs.	296	74	74	74	74
Cluster N	74	74	74	74	74
Pseudo R^2	.237	.012	.034	.007	.003
Log-likelihood	-235.049	-69.817	-49.86	-50.686	-54.934

Ordered logit regression. The dependent variable is the session level average of expectations: $\bar{\alpha}^z$. The sample includes all sessions in treatments T1*neutral*, T1*positive* and T1*negative*. Column 1 pools the four values of $\bar{\alpha}^z$ for each session. Columns 2-5 analyse separately the values of $\bar{\alpha}^1$, $\bar{\alpha}^2$, $\bar{\alpha}^3$, and $\bar{\alpha}^4$, respectively. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors are reported in parenthesis. Standard errors are corrected for clustering at the session level in column 1.

In table 23 we show that there are no treatment effects on contributions c_i^z. Tables 24 and 25 in the appendix confirm that we are equally unable to find treatment effects when we analyse each contribution decision separately, or when we estimate model specification 9. As argued above, however, this *does not* constitute evidence against the hypothesis that guilt aversion influences public good contributions in networks.

Finally, we study prediction 3. In table 9 we show that matches between contributions and average group expectations are more likely in T1*neutral* than in T0 by about 7 percentage points (34 percent), an effect significant at the 10 percent level. When we add controls or restrict to high understanding players, the coefficient drops to 6 percentage points and loses statistical significance. This result is consistent with inaccuracy in second order beliefs: players with an inaccurate prior fail to match true group expectations when these are not disclosed in T0.

A higher frequency of matches does not translate in a higher level of contributions. Tobit regressions reported in table 26 show that the level of contributions is in fact not higher in T1*neutral* than in T0. When we try to separately look at changes in the intercept and slope of the profiles, we find that in T1*neutral* the intercept is somewhat higher and the slope less steep. Neither of these effects is however measured with sufficient statistical precision.

Table 9: Linear probability model: match between c_i^z and $\bar{\alpha}^z$ in T1*neutral* and T0

	(1)	(2)	(3)	(4)
T1*neutral*	.072	.063	.068	.065
	(.038)*	(.040)	(.058)	(.061)
Const.	.215	.259	.247	.415
	(.031)***	(.105)**	(.044)***	(.163)**
Obs.	1524	1332	700	616
Cluster N	49	49	48	47
Controls		✔		✔
High understanding			✔	✔

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contribution c_i^z. The sample includes all subjects in T1*neutral* and T0. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Result 5. *In T1*neutral*, players are 6-7 percentage points more likely to set* $c_i^z = \bar{\alpha}^z$ *than players in T0. As group expectations reflect contributions in T0, players in T1*neutral *do not contribute higher amounts than players in T0.*

6 Conclusion

We play a one-shot public good game over an exogenous star network with farmers in rural India. The network determines who benefits from the public good contributions of each player. The star network is thus characterised by a strong asymmetry: contributions by the centre of the star benefit each of the spokes, while contributions by the spokes benefit only the centre player. This makes the centre player particularly effective at raising aggregate welfare. We use the strategy method to obtain from each player a contribution decision for the case where the player is assigned to the spoke position *and* for the case where the player is assigned to the centre of the star. The centre of the star is further allowed to condition his contribution decision on the (rounded) average contribution of the spokes.

We hypothesise that farmers are influenced in their contribution decisions by what they think other farmers expect them to do. This follows from the model of guilt aversion proposed by the literature in behavioural game theory. We elicit players' expectations about the contribution profiles of the centre of the star and disclose average expectations in randomly chosen sessions. In two further treatments, we attempt an experimental manipulation of the expectations of some of the players, to exogenously modify the average that we disclose and study the response of the remaining players. Within treatment, we randomly vary the rate of return to investing in the public good.

We find that, when in the position of the centre of the star, farmers choose contribution profiles that match the average contribution of the spokes and expect other farmers to choose similar profiles as well. This corresponds to findings in experiments with homogeneous groups. A key contribution of this study is to show that such profiles, usually referred to as "conditional cooperation", are also chosen by the centre player of a star network- a setting characterised by substantial heterogeneity across players.

When we disclose average expectations, players match their contributions with the disclosed values in 42 percent of the cases. An increase in the rate of return, which determines the monetary cost of contributing one more unit to the public good, is associated with a large (11 percentage points) increase in the frequency of matches for high understanding players. This effect is predicted by the model of guilt aversion. The average degree in the real-world network that connects farmers in the same session is a moderating factor: at the 90th percentile of average degree, the effect grows to almost 30 percentage points.

Farmers match their contributions to group expectations less frequently (6-7 percentage points) when group expectations are not disclosed, suggesting that some farmers hold inaccurate beliefs about what players in the network expect from the centre of the star. This effect is not associated with a related change in average public good investment by the centre player.

Our results carry implications for policy and several leads for future research. First, when players are conditionally cooperative, public good games admit only equilibria characterised by symmetric contribution levels. Our findings suggest that individuals are likely to deviate from asymmetric contribution configurations even when they occupy the high-efficiency central position in a network. This is an important point for the design of public policies that require cooperation from selected, socially central individuals in the field, such as injection points for the diffusion of innovations [Ben Yishay and Mobarak, 2012, Berg et al., 2013].

A second important lesson is about the provision of information about the expectations of other players in the network. This treatment generates more matches between contributions and average expectations, but does not lead to higher contribution levels. In a widely cited study, Jensen [2010] documents significant improvements in schooling attainment following an intervention that informs students with inaccurately low priors about statistically measured returns to schooling. On the contrary, information provision is not sufficient to improve welfare in our experiment. The expectations we disclose reflect prevalent levels of pro-sociality. For example, they do not forecast that the player at the centre of star will contribute above strict conditional cooperation. If the policy maker aims to induce contributions above conditional cooperation from central players, separate interventions to incentivise the centre of the star are required. Disclosure of information about expectations can be best used to entrench the behavioural change initially generated by means of incentives.

In terms of future research, we believe that this study illustrates the potential for using the strategy method to study public good contributions in heterogeneous groups. We envisage further exploration of specific dimensions of network heterogeneity. For example, as the sociological literature has long emphasised the importance of brokers for aggregate network outcomes, the effects of between-group centrality can be separated from those of degree centrality. Through the strategy method the researcher can both investigate how the behaviour of a specific individual varies when his position in an exogenous network changes, and how the contribution profiles of individuals correlate with the position they occupy in real-world networks. Other dimensions of heterogeneity that are not related to features of the network can also be explored.

Further, in our study we find evidence in support of a role of guilt aversion in determining public good contributions in networks. We also uncover the moderating influence of the structure of the real-world network that links study participants. These results lend weight to models of decision utility that incorporate expectations and socially-determined moderating factors. The development and empirical validation of such models is a particularly promising direction for future research that wants to understand within-individual variation in pro-social behaviour across contexts. This effort will help determine the scope for welfare-improving policy interventions that promote pro-social behaviour in different settings. More research is needed, including, in particular, direct measurement of first- and second-order expectations and further laboratory tests of the manipulability of expectations and their causal influence on behaviour. Field settings where participants are linked through a rich and varied web of connections are particularly appropriate to study how social structure moderates these effects.

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7 Appendix

7.1 Figures

Figure 7: Oneness question

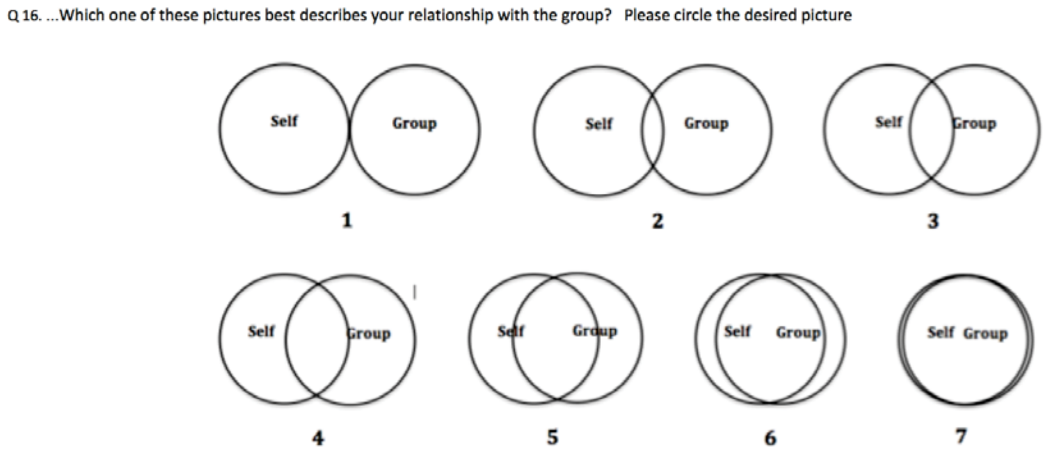


Figure 8: Histogram of self-reported oneness

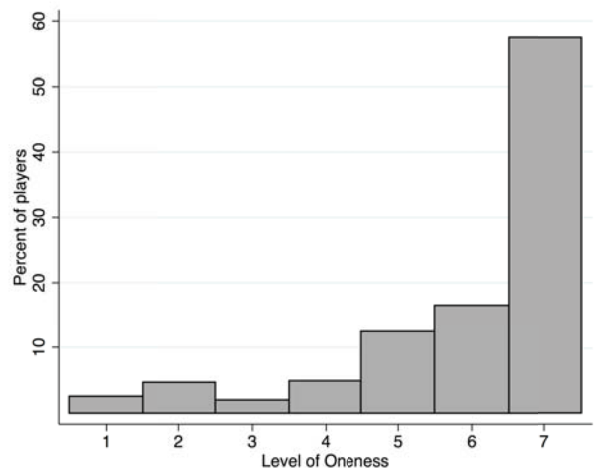
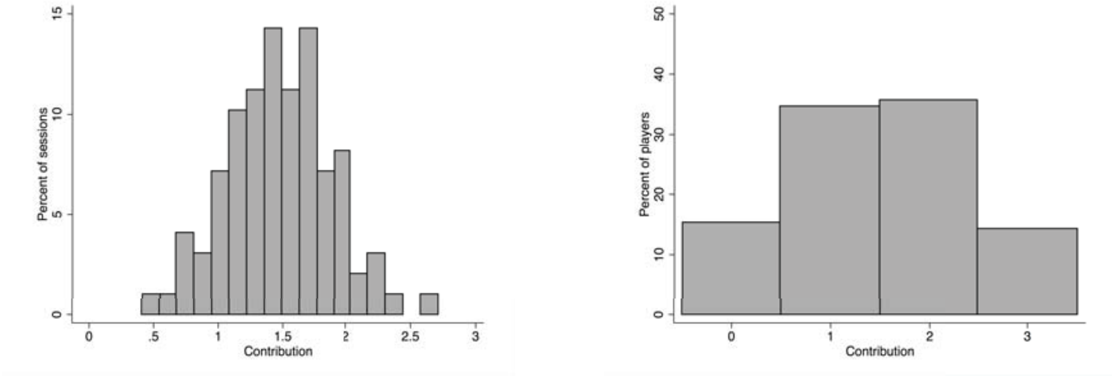


Figure 10: Final contributions



(a) Session average of spoke players contribution (b) Centre player contribution

Figure 9: Cumulative distribution of mistakes

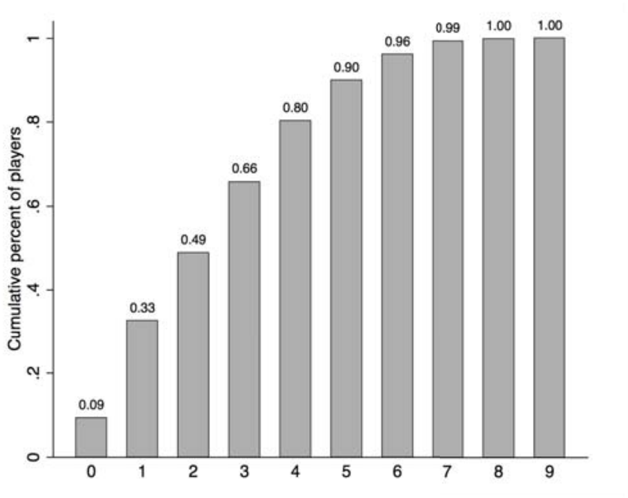


Figure 11: Archetypal expectation profiles, by understanding

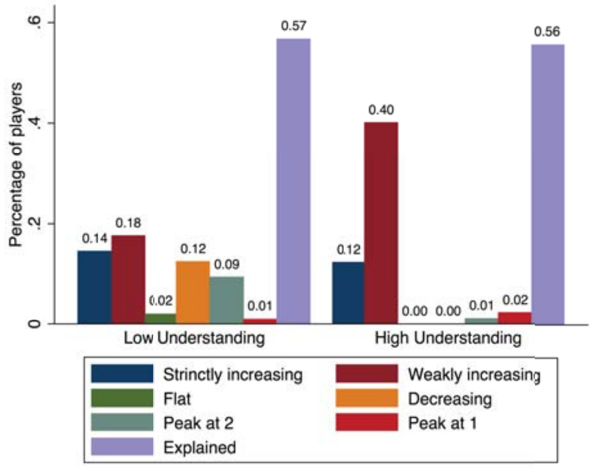


Figure 12: Average values of contributions and expectations

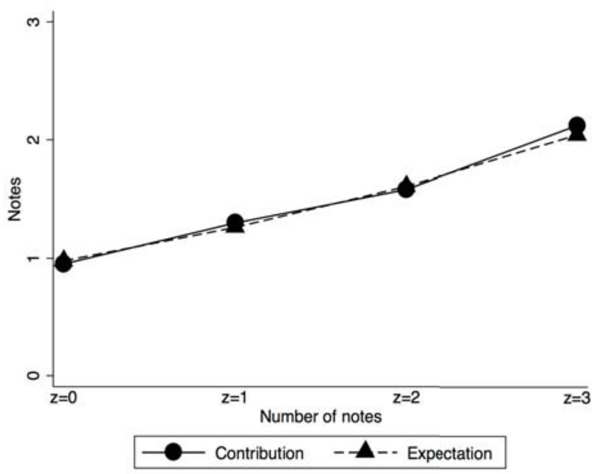


Figure 13: Probability $\alpha^z_{i,s} = \sum_{j \in N_s \setminus i} \frac{c^z_{j,s}}{7}$

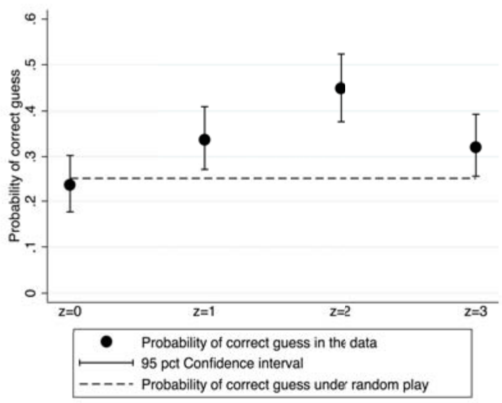
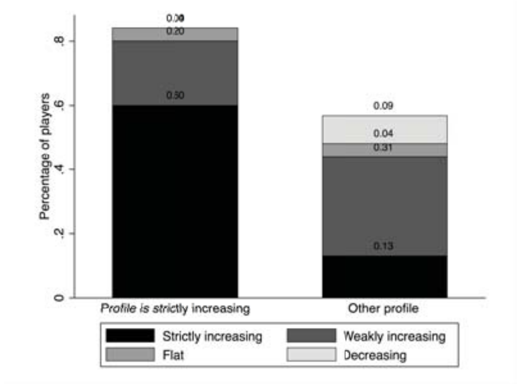
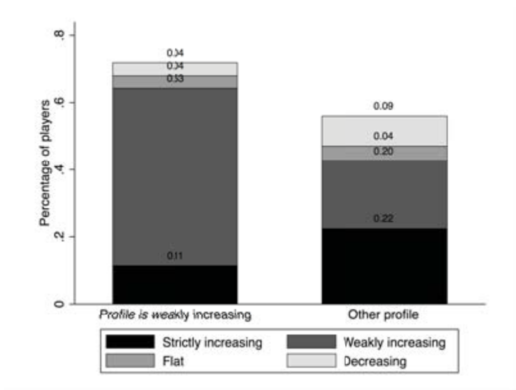


Figure 14: Expectation profiles by player's contribution profile

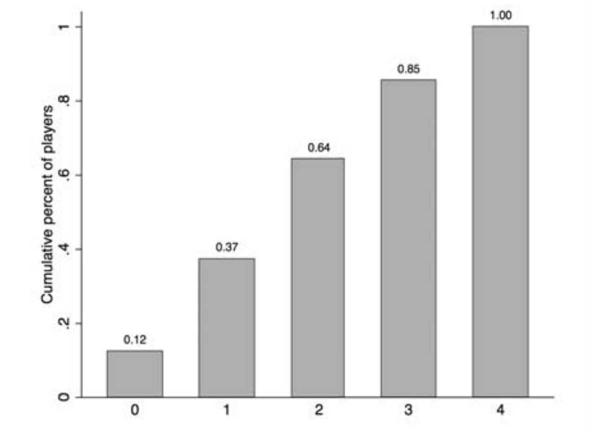


(a) By strictly increasing contribution profile



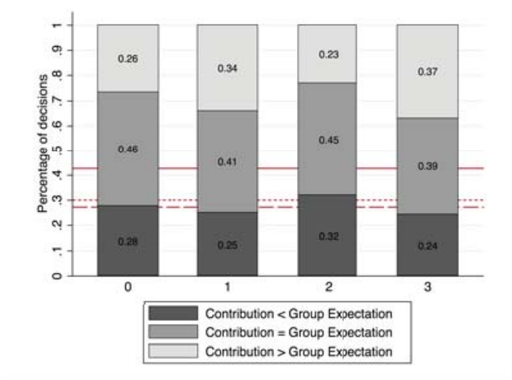
(b) By weakly increasing contribution profile

Figure 15: Cumulative distribution of $e_i = \sum_{z=0}^{3} I\left(c_{i,s}^{z} = \alpha_{i,s}^{z}\right)$

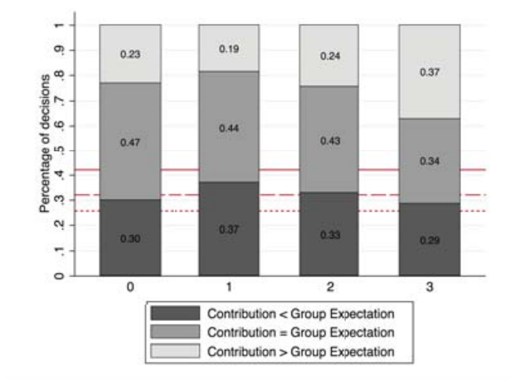


7.2 Tables

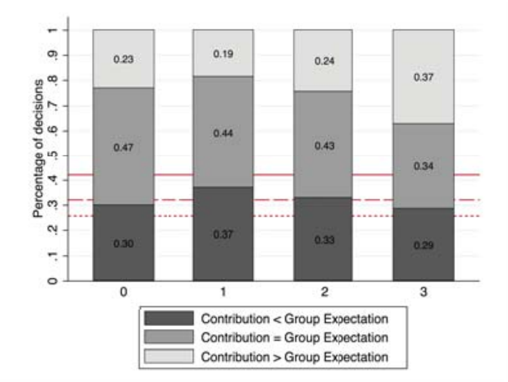
Figure 16: Match between contribution c_i^z and group expectations $\bar{\alpha}^z$



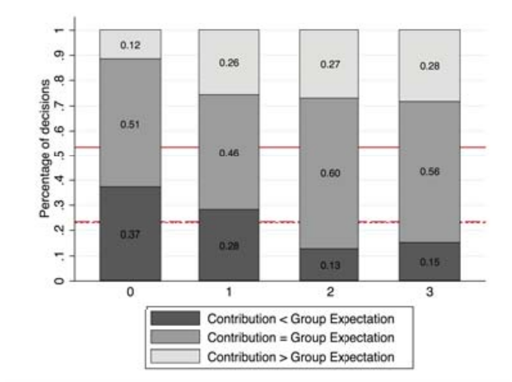
(a) Full sample, r= $\frac{3}{5}$



(b) Full sample, r= $\frac{3}{5}$



(c) High understanding players, r= $\frac{3}{5}$



(d) High understanding players, r= $\frac{4}{5}$

Note. The continuous line in the background gives the percentage of matches between contribution c_i^z and group expectations $\bar{\alpha}^z$ when we pool over all four decisions. The long dashed line indicates the percentage of decisions where $c_i^z < \bar{\alpha}^z$. The short dashed line indicates the percentage of decisions where $c_i^z > \bar{\alpha}^z$.

Figure 17: Treatment effect at different percentiles of average session-level degree

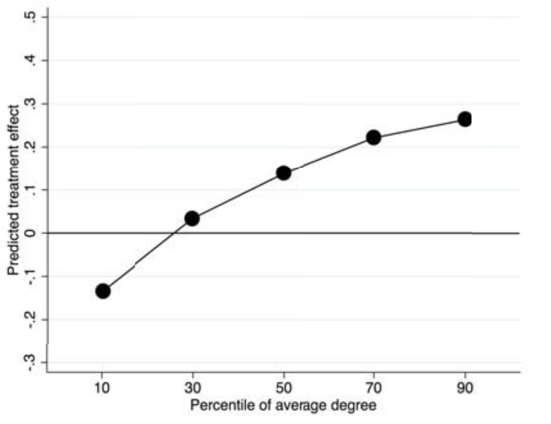


Table 10: Balance test 1

	Age	UpperCaste	HigherEdu	LandOwned	LandCult	NetSize	Oneness	Understanding	SessionN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T1	-.605	.099	-.019	-.785	-.177	-.624	-.169	.099	-.032
	(1.421)	(.072)	(.069)	(.597)	(.551)	(.706)	(.228)	(.253)	(.159)
T2p	.320	.013	-.021	.161	-.137	.505	-.180	-.080	.008
	(1.358)	(.087)	(.070)	(.752)	(.592)	(.781)	(.217)	(.265)	(.156)
T2n	-.447	.037	-.016	-.518	-.183	-.164	-.090	-.173	.083
	(1.382)	(.078)	(.062)	(.608)	(.547)	(.660)	(.181)	(.250)	(.138)
Obs.	760	745	748	761	757	744	747	765	98

OLS regressions. The dependent variable is indicated in the row's name. "HigherEdu" is a dummy that takes the value of 1 if the respondent has completed secondary school. "Upper caste" is a variable that takes value of 1 if respondent is not from a schedule caste, a scheduled tribe or an Other Backward Caste. "LandCult" is the area of land cultivated in hectares. "NetSize" is the self reported number of peers with whom the farmer exchanges advice on agricultural matters. Oneness is a number from 1 to 7. Higher numbers reflect an increasing feeling of oneness. Understanding refers to the number of mistakes in the initial understanding questions. The last column is a regression over a session level outcome-"SessionN"- the number of participants in each session. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors clustered at the session level reported in parentheses in columns 1-8. Robust standard errors are reported for the regression in column 9.

Table 11: Balance test 2

	Age	UpperCaste	HigherEdu	LandOwned	LandCult	NetSize	Oneness	Understanding	SessionN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T0	.605	-.099	.019	.785	.177	.624	.169	-.099	.032
	(1.421)	(.072)	(.069)	(.597)	(.551)	(.706)	(.228)	(.253)	(.159)
T2p	.925	-.086	-.002	.946	.040	1.129	-.011	-.179	.040
	(1.296)	(.082)	(.069)	(.641)	(.521)	(.801)	(.234)	(.251)	(.145)
T2n	.157	-.062	.003	.267	-.007	.460	.079	-.272	.115
	(1.322)	(.073)	(.062)	(.464)	(.470)	(.683)	(.201)	(.234)	(.125)
Obs.	760	745	748	761	757	744	747	765	98

OLS regressions. The dependent variable is indicated in the row's name. "HigherEdu" is a dummy that takes the value of 1 if the respondent has completed secondary school. "Upper caste" is a variable that takes value of 1 if respondent is not from a schedule caste, a scheduled tribe or an Other Backward Caste. "LandCult" is the area of land cultivated in hectares. "NetSize" is the self reported number of peers with whom the farmer exchanges advice on agricultural matters. Oneness is a number from 1 to 7. Higher numbers reflect an increasing feeling of oneness. Understanding refers to the number of mistakes in the initial understanding questions. The last column is a regression over a session level outcome-"SessionN"- the number of participants in each session. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors clustered at the session level reported in parentheses in columns 1-8. Robust standard errors are reported for the regression in column 9.

Table 12: Balance test 3

	Age	UpperCaste	HigherEdu	LandOwned	LandCult	NetSize	Oneness	Understanding	SessionN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T0	-.320	-.013	.021	-.161	.137	-.505	.180	.080	-.008
	(1.358)	(.087)	(.070)	(.752)	(.592)	(.781)	(.217)	(.265)	(.156)
T1	-.925	.086	.002	-.946	-.040	-1.129	.011	.179	-.040
	(1.296)	(.082)	(.069)	(.641)	(.521)	(.801)	(.234)	(.251)	(.145)
T2n	-.768	.024	.005	-.679	-.046	-.669	.090	-.093	.075
	(1.254)	(.087)	(.062)	(.651)	(.517)	(.761)	(.189)	(.247)	(.121)
Obs.	760	745	748	761	757	744	747	765	98

OLS regressions. The dependent variable is indicated in the row's name. "HigherEdu" is a dummy that takes the value of 1 if the respondent has completed secondary school. "Upper caste" is a variable that takes value of 1 if respondent is not from a schedule caste, a scheduled tribe or an Other Backward Caste. "LandCult" is the area of land cultivated in hectares. "NetSize" is the self reported number of peers with whom the farmer exchanges advice on agricultural matters. Oneness is a number from 1 to 7. Higher numbers reflect an increasing feeling of oneness. Understanding refers to the number of mistakes in the initial understanding questions. The last column is a regression over a session level outcome-"SessionN"- the number of participants in each session. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors clustered at the session level reported in parentheses in columns 1-8. Robust standard errors are reported for the regression in column 9.

Table 13: Most frequently chosen contribution profiles in T0. All players

Contribution profile c_i	**Percentage**
0123	19.3
0013	5.9
3210	3.7
0122	3.2
0000	2.7
0012	2.7
0223	2.1
1233	2.1
3123	2.1

Note. A strategy is indicated by a four digit code. Code 0123, for example, indicates the strategy where player i chooses: $c_i^0 = 0$, $c_i^1 = 1$, $c_i^2 = 2$ and $c_i^3 = 3$. We only include strategies played by at least 2 percent of the players in T0.

Table 14: Most frequently chosen contribution profiles in T0. High understanding players

Contribution profile c_i	**Percentage**
0123	18.9
0013	10
0000	4.4
0012	4.4
0122	3.3
0333	3.3
1233	3.3
3333	3.3
0022	2.2
0112	2.2
0323	2.2
3123	2.2
3223	2.2

Note. A strategy is indicated by a four digit code. Code 0123, for example, indicates the strategy where player i chooses: $c_i^0 = 0$, $c_i^1 = 1$, $c_i^2 = 2$ and $c_i^3 = 3$. We restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. We only include strategies played by at least 2 percent of the high understanding players.

Table 15: Most frequently chosen expectation profiles in T0. All players

Expectation profile α_i	**Percentage**
0123	13.4
0013	4.8
0012	4.3
0112	2.7
0212	2.1
0213	2.1
3122	2.1
3123	2.1
3210	2.1
3223	2.1

Note. An expectation profile is indicated by a four digit code. Code 0123, for example, indicates the expectation profile where player i chooses: $\alpha_i^0 = 0$, $\alpha_i^1 = 1$, $\alpha_i^2 = 2$ and $\alpha_i^3 = 3$. We only include expectation profiles chosen by at least 2 percent of players.

Table 16: Probit regression: robustness of tobit assumption

	$c_i^z > 0$	$c_i^z > 0$	$c_i^z = 3$	$c_i^z = 3$
	(1)	(2)	(3)	(4)
Spoke average	.450 (.065)***	.566 (.081)***	.263 (.059)***	.375 (.059)***
T1	.172 (.125)	.151 (.166)	-.082 (.138)	-.347 (.210)*
T1*Spoke average	.034 (.075)	-.007 (.097)	-.047 (.065)	-.012 (.075)
Const.	-.016 (.106)	-.265 (.145)*	-1.052 (.120)***	-1.237 (.170)***
Obs.	3060	1496	3060	1496
Cluster N	98	97	98	97
Pseudo R^2	.125	.163	.034	.088
Log-likelihood	-1456.069	-742.678	-1583.694	-667.209
High understanding.		✔		✔

Probit regression. The dependent variable is dummy variable indicated on the top of each column. Columns 2 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table 17: Linear probability model: match between c_i^z and α_i^z

	t1	t2	t3	t4
	(1)	(2)	(3)	(4)
High Rate of Return	.019	.005	.024	.023
	(.036)	(.037)	(.049)	(.051)
Const.	.596	.520	.607	.583
	(.044)***	(.129)***	(.071)***	(.204)***
Obs.	1152	1036	592	532

OLS regression.The dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \alpha_i^z$. "High rate of return" is a dummy for whether the session value of r is $\frac{4}{5}$. The sample includes all players who have received message neutral 2 in treatments T1*neutral*, T1*positive*, T1*negative*. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. All regressions include dummies for whether spoke average z is equal to 1, 2, or 3 and for whether treatment is T1*positive* or T1*negative*. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level.

Table 18: The effect of high rate of return on the level of contributions and expectations

	Contributions c_i^z	Contributions c_i^z	Expectations α_i^z	Expectations α_i^z	Group expectations $\bar{\alpha}_i^z$
	(1)	(2)	(3)	(4)	(5)
Spoke average	.678	.850	.748	1.149	1.498
	(.058)***	(.076)***	(.073)***	(.087)***	(.181)***
High Rate of Return	.112	.193	.244	.221	.183
	(.150)	(.177)	(.138)*	(.185)	(.320)
Const.	.341	-.214	.131	-.668	
	(.153)**	(.185)	(.162)	(.203)***	
Obs.	1152	592	1152	592	296
Cluster N	74	74	66	66	74
Pseudo R^2	.055	.092	.055	.128	.234
Log-likelihood	-1707.425	-835.488	-1703.895	-799.434	-236.215
Controls					
High Understanding		✔		✔	

The dependent variable is indicated on top of each column. Columns 1-4 report estimates from a tobit regression, with an upper limit of 3 and a lower limit of 0. The sample includes all players who have received neutral message 2 in treatments T1*neutral*, T1*positive*, T1*negative*. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Column 5 reports the results of an ordered logit regression over session-level expectation averages $\bar{\alpha}^z$. "High rate of return" is a dummy for whether the session value of r is $\frac{4}{5}$. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors are reported in parenthesis. Standard errors are corrected for clustering at session level in columns 1-4.

Table 19: Linear probability model: match between c_i^z and $\bar{\alpha}^z$. Moderating factors

	(1)	(2)	(3)	(4)	(5)	(6)
High Rate of Return	.023	.100	.023	.104	.024	.111
	(.042)	(.057)*	(.043)	(.057)*	(.043)	(.058)*
Average session degree	.006	.027				
	(.028)	(.039)				
Degree			-.001	.007		
			(.011)	(.016)		
Oneness					.003	.008
					(.013)	(.018)
Const.	.333	.176	.375	.301	.372	.310
	(.189)*	(.264)	(.084)***	(.121)**	(.083)***	(.107)***
Obs.	1144	584	1144	584	1132	588
Cluster N	73	65	73	65	74	66
High understanding		✔		✔		✔

OLS regression.The dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha^z}$. "Degree" is a variable that reports the number of other farmers in the session that the player knows. "Average degree" is the session-level average of degree. "Oneness" is the self-reported value of oneness. The sample includes all players who have received message neutral 2 in treatments T1*neutral*, T1*positive*, T1*negative*. In columns 2, 4 and 6 the analysis is restricted to players who have made 2 mistakes or less in the initial understanding questions. All regressions include dummies for whether spoke average z is equal to 1, 2, or 3, for whether treatment is T1*positive* or T1*negative* and for whether $r = \frac{4}{5}$. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 20: Linear probability model: match between c_i^z and $\bar{\alpha}^z$. Heterogeneous treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)
High Rate of Return	-.471	-.908	.071	.100	.172	.426
	(.311)	(.401)**	(.136)	(.188)	(.141)	(.170)**
Average session degree	-.033	-.050				
	(.038)	(.051)				
High Rate of Return * average degree	.082	.167				
	(.052)	(.067)**				
Degree			.003	.006		
			(.012)	(.022)		
High Rate of Return * degree			-.008	.0005		
			(.022)	(.032)		
Oneness					.015	.039
					(.017)	(.021)*
High Rate of Return * oneness					-.025	-.053
					(.024)	(.031)*
Const.	.564	.631	.352	.302	.301	.125
	(.238)**	(.325)*	(.089)***	(.145)**	(.099)***	(.105)
Obs.	1144	584	1144	584	1132	588
Cluster N	73	65	73	65	74	66
High understanding		✔		✔		✔

OLS regression.The dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha^z}$. "Degree" is a variable that reports the number of other farmers in the session that the player knows. "Average degree" is the session-level average of degree. "Oneness" is the self-reported value of oneness.The sample includes all players who have received message neutral 2 in treatments T1*neutral*, T1*positive*, T1*negative.* In columns 2, 4 and 6 the analysis is restricted to players who have made 2 mistakes or less in the initial understanding questions. All regressions include dummies for whether spoke average z is equal to 1, 2, or 3, for whether treatment is T1*positive* or T1*negative* and for whether $r = \frac{4}{5}$. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 21: Ordered logit regression over expectations α_i^z

	(1)	(2)	(3)	(4)
T1*positive*	-.173	-.167	-.073	-.050
	(.145)	(.158)	(.179)	(.211)
T1*negative*	-.387	-.446	-.208	-.229
	(.169)**	(.182)**	(.251)	(.303)
Obs.	1160	1040	544	488
Cluster N	74	74	66	64
Pseudo R^2	.003	.009	.0008	.006
Log-likelihood	-1598.649	-1425.325	-742.76	-663.543
Controls		✔		✔
High Understanding			✔	✔

Ordered logit regression. The dependent variable is expectation α_i^z. The sample includes all subjects in T1*neutral*, T1*positive* and T1*negative* who have received message 1 (neutral in T1*neutral*, positive in T1*positive* and negative in T1*negative*). Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 22: Ordered logit regression over expectations α_i^z

	α_i^0	α_i^1	α_i^2	α_i^3
	(1)	(2)	(3)	(4)
T1*positive*	-.183	-.301	-.172	-.007
	(.281)	(.277)	(.272)	(.247)
T1*negative*	-.326	-.589	-.554	-.217
	(.313)	(.326)*	(.282)**	(.253)
Obs.	290	290	290	290
Cluster N	74	74	74	74
Pseudo R^2	.002	.006	.006	.001
Log-likelihood	-324.074	-381.098	-346.641	-362.719

Ordered logit regression. The dependent variable is expectation α_i^z. The sample includes all subjects in T1*neutral*, T1*positive* and T1*negative* who have received message 1 (neutral in T1*neutral*, positive in T1*positive* and negative in T1*negative*). Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 23: Tobit regression model 8 over contributions c_i^z

	(1)	(2)	(3)	(4)
T1*positive*	-.044	-.061	-.013	-.144
	(.192)	(.203)	(.228)	(.248)
T1*negative*	.090	.116	.237	.171
	(.160)	(.175)	(.214)	(.250)
Const.	1.413	1.479	1.089	1.566
	(.109)***	(.387)***	(.167)***	(.718)**
Obs.	1152	1036	592	532
Cluster N	74	73	66	62
Pseudo R^2	.0003	.003	.001	.01
Log likelihood	-1805.97	-1620.165	-919.444	-819.762
Controls		✔		✔
High Understanding			✔	✔

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contribution decision c_i^z. The sample includes all subjects in T1*neutral*, T1*positive* and T1*negative* who have received message 2 neutral 2. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table 24: Tobit regression model 8 over contributions c_i^z, by spoke average

	c_i^0	c_i^1	c_i^2	c_i^3
	(1)	(2)	(3)	(4)
T1*positive*	.207	.026	-.078	-.301
	(.667)	(.233)	(.158)	(.314)
T1*negative*	.043	.231	-.005	-.011
	(.588)	(.203)	(.168)	(.297)
Const.	-.566	1.192	1.609	2.643
	(.470)	(.133)***	(.115)***	(.219)***
Obs.	288	288	288	288
Cluster N	74	74	74	74
Pseudo R^2	.0002	.002	.0004	.002
Log-likelihood	-366.395	-438.4	-397.619	-412.407

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contribution decision c_i^z. The sample subjects in T1*neutral*, T1*positive* and T1*negative* who have received neutral message 2. Columns 1-4 analyse separately the values of c_i^1, c_i^2, c_i^3, and c_i^4, respectively. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 25: Tobit regression model 9 over contributions c_i^z

	(1)	(2)	(3)	(4)
T1*positive*	.147	.057	-.107	-.445
	(.333)	(.342)	(.430)	(.447)
T1*negative*	.134	.170	-.087	-.240
	(.285)	(.292)	(.375)	(.353)
Spoke average	.734	.703	.758	.660
	(.102)***	(.100)***	(.148)***	(.148)***
T1*positive* * spoke average	-.132	-.086	.055	.185
	(.145)	(.146)	(.210)	(.219)
T1*negative* * spoke average	-.037	-.044	.201	.257
	(.135)	(.135)	(.180)	(.180)
Const.	.303	.408	-.045	.576
	(.205)	(.385)	(.297)	(.717)
Obs.	1152	1036	592	532
Cluster N	74	73	66	62
Pseudo R^2	.055	.054	.094	.094
Log-likelihood	-1706.765	-1537.37	-834.164	-749.935
Controls		✔		✔
High Understanding			✔	✔

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contribution decision c_i^z. The sample includes all subjects in T1*neutral*, T1*positive* and T1*negative* who have received neutral message 2. Columns 3 and 4 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.

Table 26: Tobit regression over contributions c_i^z in T1*neutral* and T0

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1*neutral*	.059	.076	-.180	-.077	.204	.288	.139	.381
	(.158)	(.167)	(.270)	(.303)	(.302)	(.314)	(.402)	(.408)
Spoke average					.755	.807	1.035	1.100
					(.113)***	(.111)***	(.115)***	(.116)***
T1*neutral* * spoke average					-.096	-.139	-.200	-.289
					(.145)	(.149)	(.163)	(.165)*
Const.	1.468	1.109	1.342	.822	.323	-.135	-.231	-.856
	(.133)***	(.428)***	(.246)***	(.671)	(.230)	(.496)	(.333)	(.745)
Obs.	1524	1332	700	616	1524	1332	700	616
Cluster N	49	49	48	47	49	49	48	47
Pseudo R^2	.00006	.002	.0005	.007	.047	.052	.074	.084
Log-likelihood	-2386.04	-2079.048	-1085.009	-948.697	-2274.715	-1975.799	-1005.009	-874.526
Controls		✔		✔		✔		✔
High understanding			✔	✔			✔	✔

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contribution c_i^z. The sample includes all subjects in T1*neutral* and T0. Columns 3, 4, 7 and 8 restrict the analysis to players who have made 2 mistakes or less in the initial understanding questions. Columns 2 , 4, 6 and 8 include controls for the players' age, area of land owned, area of land cultivated, number of contacts in real information networks, self-reported oneness with the group, and dummies for having completed secondary education, for being Hindu, and for belonging to a non backward caste. Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%. Standard errors corrected for clustering at session level are reported in parenthesis.