Expectations, Network Centrality, and Public Good Contributions:

Experimental Evidence from India*

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Abstract

Do individuals in a position of social influence contribute more to public goods than their less connected partners? Can we motivate these influential individuals by disclosing how others expect them to act? To answer these questions, we play a public good game on a star network. The experimental design is such that efficiency and equality considerations should motivate central players to contribute more than others. Using a subject population familiar with contributions to public goods on social networks, we find that central players contribute just as much as the average of other players, leading to a large loss of efficiency. When we disclose the expectations of other players, we find that central players often adjust their contributions to meet the expectations of the group. Expectations disclosure leads to higher contributions in groups that have weak social ties outside of the experiment. In groups where ties are strong, it has no significant effect. This evidence casts doubt on the idea that individuals who, by their social position, can contribute more effectively to the public good rise to the challenge by contributing more than others. In some, but not all social groups, these individuals can be motivated to increase contributions by disclosing the expectations of others.

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1 Introduction

Individuals who occupy a central position in social networks can often contribute more effectively to the welfare of others. Social centrality helps them to disseminate information widely and to influence behaviour (DeMarzo et al., 2003; Golub and Jackson, 2010; Banerjee et al., 2013), to facilitate transactions (Breza et al., 2014), and to take up a leadership role (Bonacich, 1987; Burt, 2010; Labonne et al., 2015). Further, these individuals can obtain information, favours and other forms of benefit from their interactions with others (Besley et al., 2011; Alatas et al., 2013; Banerjee et al., 2014). This means that they stand to gain disproportionately from the public goods that are distributed over networks. Because of these reasons, it is often anticipated that central individuals will be willing to make greater contributions to social welfare than other members of the community. For example, in policy interventions central individuals are often asked to take costly unilateral actions to diffuse information, mobilise communities and initiate social change (Ben Yishay and Mobarak, 2012; Berg et al., 2013; Kondylis et al., 2017; Beaman et al., 2015).

It is unclear, however, whether people are prepared to act more pro-socially when they occupy a position of social centrality. We have also little evidence on the strategies that can be used to motivate such individuals to contribute more to the public good. These issues have important implications for policy. If people behave more pro-socially when they are in a position of social influence, the process by which these individuals are selected or incentivised matters little. In contrast, if people do not naturally behave more pro-socially when they acquire social influence, setting up selection and incentive schemes becomes important.

We investigate these questions using a lab experiment in the field, inspired by the theoretical work of Bramoullé and Kranton (2007). In this experiment, subjects are randomly assigned to a position in a star network and then asked to contribute to a public good. By design, the contribution of the centre player benefits all individuals located at the spokes, while the contributions of the spokes only benefit the centre. As we explain below, both considerations of efficiency *and* equality should motivate the star centre to contribute more than the spokes.[1] We elicit contribution choices using the strategy method: before network positions are announced, each subject decides how much he would like to contribute if he is assigned to the centre of the star, and how much he would like to contribute if he is assigned to the spoke position.

During the experiment, we collect information on how much each subject expects the centre to contribute. In selected sessions we disclose this information publicly before contribution choices are made. A simple model of guilt aversion (Battigalli and Dufwenberg,

[1] In our set-up the optimal strategy for a selfish player is not to contribute to the public good. Thus a selfish player would make zero contributions irrespective of his position in the network. This is a key difference with Bramoullé and Kranton (2007), who study a model where positive contributions can be optimal for selfish players and where the structure of the network determines selfish play in equilibrium. In our experiment, the structure of the network only matters for other-regarding players.

2007; Dufwenberg et al., 2011) predicts that public disclosure should result in a closer correspondence between contributions and expectations. Contribution levels should also increase if subjects underestimate how much is expected from central players. This could be the case, for example, if people form these beliefs through some forms of motivated reasoning – an hypothesis that has received support in the recent literature (Epley and Gilovich, 2016).

We implement the experiment with randomly selected adult male farmers from villages in the Indian state of Maharashtra. Charness et al. (2013) highlight the importance of collecting experimental evidence on preferences across different populations (Henrich et al., 2006; Falk et al., 2015; L'Haridon and Vieider, 2016). They further argue that a key advantage of running lab experiments outside of standard labs is the ability to study populations more 'attuned to the research question'. We thus choose a population where social networks informally provide many public goods (Beteille and Srinivas, 1964). For example, extension services often select members of the community – e.g, 'model farmers' – for the dissemination of valuable information about agriculture or welfare programs (Berg et al., 2013; Kondylis et al., 2017). To further investigate the external validity of our findings, we collect observational data on the social connections that participants have outside of the experiment and we use this information in the analysis.

We find that subjects assigned to be star centre contribute on average as much as the spokes. This strategy is known as 'conditional cooperation'. It is played frequently in games where subjects are equally efficient at producing the public good, and where equal contributions generate equal outcomes (Chaudhuri, 2011). In our game, however, efficiency and equality require the star centre to contribute *more* than the spokes. This suggests that conditional cooperation is played for reasons other than preferences over outcomes. One possibility is that subjects only care about meeting the expectations of others. We indeed find that subjects expect the star centre to be a conditional cooperator. We further find that conditional cooperation with spokes is similarly chosen by individuals with high network centrality outside the experiment. This suggests that our findings may generalise to settings where network centrality is socially determined.

Conditional cooperation by the star centre has a large cost in term of efficiency and equality. To show this, we compare the outcomes in the experiment to what would happen if the star centre always contributed the maximum amount. We find that experimental subjects only achieve about 50 percent of the potential gains from cooperation. If the central player contributed the maximum amount, 82 percent of the potential gains from cooperation would be achieved. Further, we find that the difference in payoff between centre and spokes would be halved if the centre contributed the maximum amount.[2] In other words, star centres have a determinant influence on aggregate payoffs, and higher

[2]When interpreting these figures, it is important to note that the centre benefits from the contributions of seven spokes, while each spoke only benefits from the contributions of the centre. Further, when the spokes contribute a positive amount, payoff differences between the centre and the spokes can be reduced by the centre, but they cannot be fully eliminated.

contributions from them would reduce inequality in payoffs. But this is not sufficient to induce higher contributions on their part.

We further find that the central player is responsive to the expectations of the other players. When we disclose these expectations, the proportion of star centre contributions that match other players' expectations goes up by a significant 11.5 percentage points. This finding is consistent with a model of guilt aversion. We also document that players match their contribution to group expectations more frequently when we increase the cost of investing in the public good, a finding that is also in line with guilt aversion.

Despite the tighter correspondence between contributions and expectations, disclosing expectations does not increase average contributions. We present evidence suggesting that this is because, in our subject population, the number of subjects who underestimate the group expectation is similar to the number of those who overestimate it. These findings, however, vary with the strength of the connections between participants outside the experiments. When participants are weakly connected with each other outside of the experiment, disclosing expectations actually increases contributions by a significant 13 percent. Conversely, when connections outside of the experiment are strong, disclosing expectations has a small negative and insignificant effect on contributions.

Finally, we show that our results are qualitatively unaffected if we run the analysis only on the subjects who demonstrated the best understanding of the rules of the experiment.

Our study contributes to several strands of literature. First, we contribute to the literature that studies the behaviour of central individuals in social networks (Banerjee et al., 2013; Breza et al., 2014; Gallo and Yan, 2015) and more generally, to the literature that studies individuals in positions of high influence, such as community and political leaders (Bonacich, 1987; Komai et al., 2007; Burt, 2010; Labonne et al., 2015). This literature has emphasised that leaders can increase cooperation and motivate effort by changing incentives, through 'leadership by example', and by communicating required behaviour or private information (Brandts and Cooper, 2007; Grossman and Baldassarri, 2012; Cartwright et al., 2013; Brandts et al., 2014; Jack and Recalde, 2015; McCannon et al., 2015). It has also documented cases in which individuals in a position of influence fail to act for the benefit of others (Ben Yishay and Mobarak, 2012). Our results help reconcile these disparate observations by showing that individuals are reluctant to take a unilaterally pro-social action (e.g., contribute to a public good when others are not contributing) even when they have been placed in a position of high influence. This suggests that leadership works most effectively when leaders are confident that their pro-social behaviour will be reciprocated

Second, we contribute to the literature on guilt aversion in two ways (Dufwenberg and Gneezy, 2000; Charness and Dufwenberg, 2006; Ellingsen et al., 2010; Bellemare et al., 2010; Dufwenberg et al., 2011). First, we present some of the first evidence for guilt aversion outside of Western populations. This is important to establish as the literature has shown that preferences can vary widely across cultures (Henrich et al., 2006;

Falk et al., 2015). Second, we test whether guilt aversion can be exploited to foster pro-social behaviour.[3] Our results highlight that this may be possible when individuals underestimate what is expected of them. In our subject population, this appears to be the case for groups that are not tightly-knit.

Finally, we contribute to a small literature that studies public good games played on networks (Fatas et al., 2010; Carpenter et al., 2012; Rosenkranz and Weitzel, 2012; Boosey and Isaac, 2016). In particular, Rosenkranz and Weitzel (2012) find that individuals assigned to a central position contribute *less* than other players in a repeated game of strategic substitutes with an interior optimum. We contribute to this literature by offering a design that is particularly amenable to the study of other-regarding motives. In our game, there is no uncertainty about the distributional consequences of actions and no scope for dynamic strategies. Further, the elicitation and disclosure of expectations allows us to test the predictions of behavioural models, such as guilt aversion, in which preferences depend on beliefs. We are also able to relate experimental play to the characteristics of subjects and their social network outside the lab. Our results suggest that low public good provision in networked communities can be due to the low social pressure felt by individuals in positions of influence. This is an important point because, in social networks, connections are typically centralised around a small number of popular nodes (Goyal, 2007; Caria and Fafchamps, 2017).

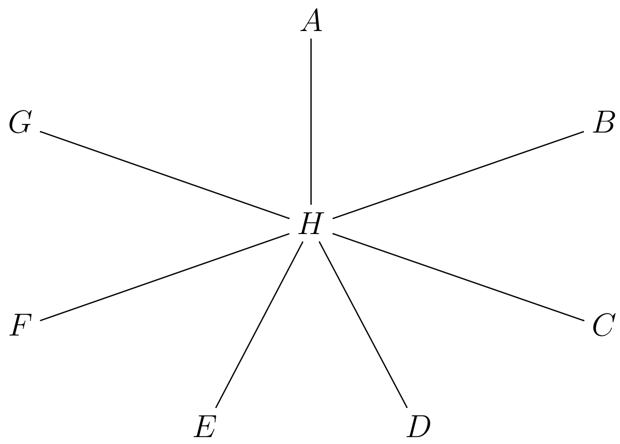
In the next section we introduce the design of the experiment. Section 3 presents theoretical predictions and discusses how we test them. Section 4 summarizes the data from the experiment. The empirical results are discussed in Section 5 while Section 6 concludes.

2 Design

We play a public good game over a network that determines who benefits from the contributions of each player. The network has the shape of a star, with one centre player and seven spokes. Links in the network cannot be changed and are undirected: if player A is linked to player H, then player H is linked to player A. Thus 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. We recruit eight subjects for each session. Each person is randomly assigned to a position in the star network.

[3] Cardella (2016) studies whether individuals strategically induce guilt in others. Our experiment differs in two important ways. First, the induction of guilt is done by a third party. Second, guilt is generated by disclosing other players' expectations (as opposed to disclosing the consequences of the subject's actions).

Figure 1: The star network



2.1 Contributions

Each player is endowed with three notes worth 50 INR each and has to decide how many notes to contribute for the provision of the public good.[4] Contribution decisions are made *before* the positions in the network are assigned. This enables us to ask players how much they would like to contribute (i) if they are assigned to the spoke position and (ii) if they are assigned to the centre position. Decision (i)- we call this the 'spoke contribution' or s_i- is an unconditional contribution decision. On the other hand, decision (ii)- we call this the 'centre contribution' or c_i- is conditional on the average contribution of the spokes. We use the letter z to refer to the (rounded) average contribution of the spokes: $z \in \{0, 1, 2, 3\}$. For each possible value of z, the player has to choose how much he would like to contribute if he is assigned to the centre position *and* the seven spokes have contributed on average z. We let c_i^z denote the contribution to the public good of player i when the spokes contribute on average 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'. Finally, we use x_i to indicate the actual contribution of player i: $x_i = s_i$ 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.

The payoff of a player i is given by:

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

where, using notation from Goyal (2007), N denotes the set of players in a session, and N_i^d identifies the subset of these players that are linked to player i. r is the rate of

[4] Players can contribute zero, one, two or three notes. Fractions of a note are not allowed. The value of the endowment- 150 INR- correspond to 7.75 USD, using an exchange rate of 0.0155 USD for one INR, and then a PPP conversion factor of 10/3. The size of the endowment is comparable to a daily wage offered in a state employment program and is in line with those of similar experiments. For example, Breza et al. (2014) report a mean payout of about 110 INR for an experiment with Indian farmers in Karnataka. The minimum a farmer can earn in our experiment is 90 INR, the maximum is 990 INR.

return to investing in the public good. We randomly vary across sessions whether r takes a low ($3/5$) or a high ($4/5$) value.

We comment on a number of features of this design. 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 otherwise preserved: $r < 1$ and hence contributing a positive amount is a dominated strategy. Further, aggregate payoffs increase monotonically with x_i and are maximised when every player contributes the whole endowment.

Second, the impact of a note contributed by player i on the total value of the public good- $r50 \times (N_i^d + 1)$- increases with the number of connections player i has. A note contributed by a spoke player generates $2 \times r50$ worth of public good. A note contributed by a centre player generates $8 \times r50$ of public good. The personal payoff cost of contributing one note to the public good, on the other hand, is the same for a spoke and for a central player. This is a very high difference in efficiency.[5]

Third, we use the strategy method twice. First, we allow players to make 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, we let players condition the latter decision 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 results that are qualitatively similar to those obtained using direct elicitation methods (Fischbacher et al., 2012). Further, the evidence collected in several studies suggests that use of the strategy method does not influence whether a treatment effect is found or not (Brandts and Charness, 2011). To keep the design simple, we do not allow players to condition their spoke decision on the contribution of the centre of the star. This asymmetry may decrease the direct comparability of the spoke and centre decisions. However, it does not affect the interpretation of the contribution profile of the centre, which is our primary object of interest.

Finally, we play with groups of eight subjects, which can be considered as a moderately large group size (for example, the meta-analysis of public good games by Zelmer (2003) reports an average group size of 6.6). Previous evidence suggests that in public good

[5] 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 of each spoke by 40 INR (i.e. it increases the total payoff of the seven spokes by 280 INR), while decreasing the centre's own payoff by 10 INR. This ratio is even more favourable than the ratio of 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. When interpreting these figures, it is important to keep in mind that the two designs are not perfectly comparable. In particular, in Charness and Rabin (2002) the dictator can have a large impact on the payoff of a single player, while in our design the centre of the star can benefit several players by a smaller amount.

games, group size has a very modest positive relationship with cooperation (Zelmer, 2003).[6] A recent paper by Nosenzo et al. (2015) finds a positive effect of group size on cooperation when the rate of return to public good investment is low, and a negative effect when the rate of return is high. Nosenzo et al. (2015) document these findings in the context of a repeated public good game. Importantly, negative group size effects tend to reduce or disappear in the first and last period of the game, which are strategically more similar to our one-shot experiment (in the first period of a repeated game, there is no history of play; in the last period of the game, there are no repeated play considerations). Barcelo and Capraro (2015) vary group size in a one-shot public good game and find a positive effect on contributions. Overall, the evidence suggests that in public good games group size effects are likely to be modest, and possibly positive. We acknowledge that our findings should be interpreted as applying to moderately large experimental groups.

2.2 Expectations

We ask each player to predict the average value of c_j^z among the other seven players, for each level of z.[7] We do this after the 'spoke contribution' decision s_i, but before 'centre contribution' decisions c_i. We use α to denote expectations. α_i^z thus records how much player i expects the other seven players to contribute when they play as centre of the star and the spokes contribute on average z notes. Formally, $\alpha_i^z = E_i\left(\sum_{j \in N \setminus i} \frac{c_j^z}{7}\right)$, where $N \setminus i$ indicates all individuals in N excluding player i. The expectation 'profile' $\alpha_i = \left(\alpha_i^0, \alpha_i^1, \alpha_i^2, \alpha_i^3\right)$ collects the four expectations elicited from player i. Finally, we refer to $\bar{\alpha}^z$ – the average of α_i^z over all eight players – as the 'group expectation'. $\bar{\alpha}^z$ indicates what is the contribution that individuals in the network, on average, expect from a player at the centre of the star.

We elicit expectations without providing monetary incentives. We have several reasons for this. First, we wish to keep the design simple to maximise understanding. Second, we are worried that incentivising expectations may distort decisions. In particular, when we disclose $\bar{\alpha}$, players may set c_i with the objective of making other players win the reward for a correct prediction. Third, incentivising expectations may trigger 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. These are serious concerns, for which there is some support in the experimental literature. For example Gächter and Renner (2010) find that incentivised expectation elicitation in a public good game changes public good contributions

[6] On the other hand, larger groups tend to cooperate less in prisoner-dilemma experiments (see for example Barcelo and Capraro (2015) and the discussion in Nosenzo et al. (2015)).

[7] All instructions are double-translated. We are careful to ensure participants understand that we refer to expectations in the sense of 'forecasts', and not of 'demands'. For each average contribution of the spoke z, we ask: 'On average, how many notes will the other players put in the common pot when they play as player H and players A to G have put on average z notes in the common pot?'. The 'common pot' is a physical holder where players have to put the notes that they would like to contribute to the public good.

compared to a control conditions where expectations are not elicited. Unicentivised expectation elicitation, on there other hand, does not affect contribution levels in the same experiment. Delavande et al. (2011) summarises several recent studies in developing countries where expectations have not been elicited with monetary incentives.

2.3 Treatments

In selected sessions, we disclose $\bar{\alpha}$ publicly on a whiteboard. The full profile is disclosed by drawing a simple table with the value of z in the first column, and the value of $\bar{\alpha}^z$ in the second column. This is done *after* eliciting expectations from each player, and *before* players take their centre contribution decisions. Subjects are not informed that the average of the expectations they report will later be disclosed to the group. This feature is important, as it rules out the possibility that farmers misreport their expectations in order to influence the behaviour of the other players.[8] It also ensures that, before the disclosure of $\bar{\alpha}$, the experimental protocol is identical across treatments. We refer to sessions where group expectations are disclosed as T-D sessions. Sessions where group expectations are not disclosed are called T-ND sessions. For each type, we run the experiment both with a high rate of return to contributions to the public good and with a low rate of return. We give more detail in the data section below.

Figure 2 summarises the order of activities during the experiment. First, players choose their spoke contribution. Second, expectations α_i about centre contributions are elicited. Then, in selected sessions, the average of α_i is disclosed publicly. Finally, players choose their centre contribution. One important feature is that the spoke contribution decision always comes before the centre decision. This makes it simpler for subjects to understand the conditional nature of the centre contribution decision.[9] As good understanding of this feature of the design is essential for our purposes, we refrain from randomising the order of the spoke and contribution decisions. A further advantage of a fixed order of play is it helps us limit the number of experimental conditions. One potential drawback is that subjects may anchor the centre contribution decision on their own spoke contribution decision. However, this is mitigated in this design because the centre has to specify a full contribution profile, which is likely to discourage anchoring on a single contribution level. Consistently with this, we show in the results section that centre contribution profiles that are fully anchored on the spoke contribution level are extremely rare (about 2.5 percent of all contribution profiles).

[8]The literature has recently started analysing the possibility that individuals may manipulate their own expectations in order to induce guilt in others (Cardella, 2016).

[9] If the order of decisions was reversed, subjects would need to condition their centre decision on the realisation of an event that is yet to happen. This would make the decision more abstract and more likely to be misinterpreted.

Figure 2: Order of activities in the experiment

3 Predictions

3.1 The contribution profile of the centre of the star

In *standard* public good games played with the strategy method, individual contributions often match the average contribution of the group (Fischbacher et al., 2001; Chaudhuri, 2011). This strategy is called conditional cooperation. In our design, this would correspond to the profile $c_i = (0, 1, 2, 3)$, or to profiles that are *weakly increasing* and *weakly lower* than the average contribution of the spokes, for example $c_i = (0, 0, 1, 2)$. We refer to the profile $c_i = (0, 1, 2, 3)$ as 'strict conditional cooperation', and to the second category of profiles as 'weak conditional cooperation'.

In standard public good games all players have equal endowments and are equally effective at creating the public good. Thus, conditional cooperation may derive from a desire to equalise payoffs or to reciprocate kind actions. In our game, however, the centre of the star has a number of reasons to contribute *more* than the other players. First, contributions by the centre of the star *reach* more players than contributions by the spokes. As a result, for same cost, the centre of the star generates an increase in the payoffs of other players that is seven times larger than that generated by a spoke. Motivated by his relative efficiency, the centre of the star may decide to contribute proportionally more than what the spokes contribute. This would result in a profile with a steeper slope than $c_i = (0, 1, 2, 3)$.[10] 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 all the spokes contribute the same positive amount, higher contributions by the centre of the star unambiguously reduce inequality in payoff among players. When all the spokes contribute zero, on the other hand, positive contributions by the centre of the star increase inequality. Inequality averse players dislike payoff differences of both types (Fehr and Schmidt, 1999). Thus a sufficiently inequality-averse player would choose to contribute nothing when the spoke contribute nothing, and to contribute all of the endowment when the spoke contribute a positive amount. The contribution profile will thus be: $c_i = (0, 3, 3, 3)$.[11]

[10]The number of notes that a player can contribute is censored at 3. The slope of the censored profile may actually be flatter than $c_i = (0, 1, 2, 3)$. For example, if the centre wants to contribute $z * 3$ for each level of z, the contribution profile is going to be: $c_i = (0, 3, 3, 3)$.

[11]We present a formal derivation in section A.1 of the Appendix. In the same section, we also present predictions generated by the models of social preferences of Bolton and Ockenfels (2000) and Charness and Rabin (2002).

Third, other players may expect the centre of the star to contribute a higher amount than everybody else, based on the considerations of relative efficiency and equality that we presented above. This can create a certain 'social pressure' on the central player, which is captured by the model of guilt aversion presented below.

3.2 Expectations disclosure and guilt aversion

To predict how individuals will respond to the disclosure of expectations we turn to the model of guilt aversion. We use the concept of 'simple guilt' from Battigalli and Dufwenberg (2007): subjects experience guilt if their actions determine a payoff for other players that is lower than what these players expect. We capture the guilt that the star centre i feels towards the spoke j with the following function[12]:

$$\begin{aligned} G_{ij}(c_i, \alpha_j, z) &= \max\{E_j[\pi_j] - \pi_j, 0\} \\ &= \max\{3 - (1-r)s_j + r\alpha_j^z - (3 - (1-r)s_j + rc_i^z), 0\} \\ &= \max\{r(\alpha_j^z - c_i^z), 0\} \end{aligned}$$

where we normalise to one the value of a note in the player's endowment and rely on the usual notation: c_i is the contribution profile of player i, α_j is the expectation profile of player j, s_j is the spoke contribution of player j, and z indicates the average contribution of all the spokes. The utility of player i is given by:

$$u_i(c_i, \alpha_j, z) = \pi_i - \frac{1}{7}\sum_{j \neq i}^{7} g_i \times G_{ij}(c_i, \alpha_j, z) \tag{2}$$

We assume that player i believes that each spoke has the same expectations, so that individual expectations coincide with the group average $\bar{\alpha}$.[13] Thus, he experiences the same guilt towards each spoke. The utility function simplifies to:

$$u_i(c_i, \bar{\alpha}, z) = \pi_i - g_i \times G_i(c_i, \bar{\alpha}, z) \tag{3}$$

where $G_i(c_i, \bar{\alpha}, z) = \max\{r(\bar{\alpha}^z - c_i^z), 0\}$. The first element in utility function (3) reflects a concern for monetary payoffs. The second element is the cost of guilt. If a player is sufficiently averse to guilt, he will align his contributions to the expectations of

[12] Battigalli and Dufwenberg (2007) distinguish between: (i) the difference between the expected payoff and the actual payoff of player j, and (ii) how much of that difference is due to the strategy chosen by player i. In our context, the two concepts coincide as the centre of the star i is the only player who has an influence on the payoff of spoke j.

[13] An alternative assumption with the same implications is that the centre feels guilt if he deviates from the average expectation of all the spokes. In the current formulation of utility in equation 2, on the other hand, the centre player wants to minimise the average of the guilt that he perceives towards each spoke. These two objectives coincide if all spokes have the same expectations.

others in order to minimise guilt. This is easily illustrated with an example. Suppose that, in this example, player i contributes an amount that is lower than what other players expect. This discrepancy makes him feel *guilty*. Increasing contributions by one note decreases the centre player's guilt by $g_i r$. It also reduces the centre's payoff by $(1-r)$. When $g_i > \frac{1-r}{r}$, the reduction in guilt outweighs the loss of monetary payoff. In this case, player i finds it optimal to contribute what the spokes expect him to contribute.

In practice, the centre of the star is uncertain about the expectations of the spokes.[14] We use β_i to denote player i's belief about the contribution that the spokes expect from the centre player: $\beta_i = E_i[\bar{\alpha}]$. In treatment T-D, we disclose $\bar{\alpha}$. Subjects with incorrect beliefs will revise these beliefs. Those who are sufficiently guilt averse, will also revise their contribution decisions in response to this.[15] As a result, a higher number of subjects in T-D will align contributions to group expectations, compared to T-ND. This is our first prediction.

Prediction 1. *Subjects in T-D are more likely than subjects in T-ND to choose contributions c_i^z that are equal to $\bar{\alpha}^z$.*

The effect of expectations disclosure on the *level* of contributions will depend on whether subjects with inaccurate priors are more likely to underestimate or overestimate group expectations. If subjects underestimate group expectations, contributions will increase on average when expectations are disclosed. On the other hand, if subjects overestimate group expectations, disclosing that less is expected from them will lead to lower contributions.

Prediction 2. *If players underestimate group expectations, contributions will be higher in T-D compared to T-ND. If players overestimate group expectations, contributions will be lower in T-D compared to T-ND.*

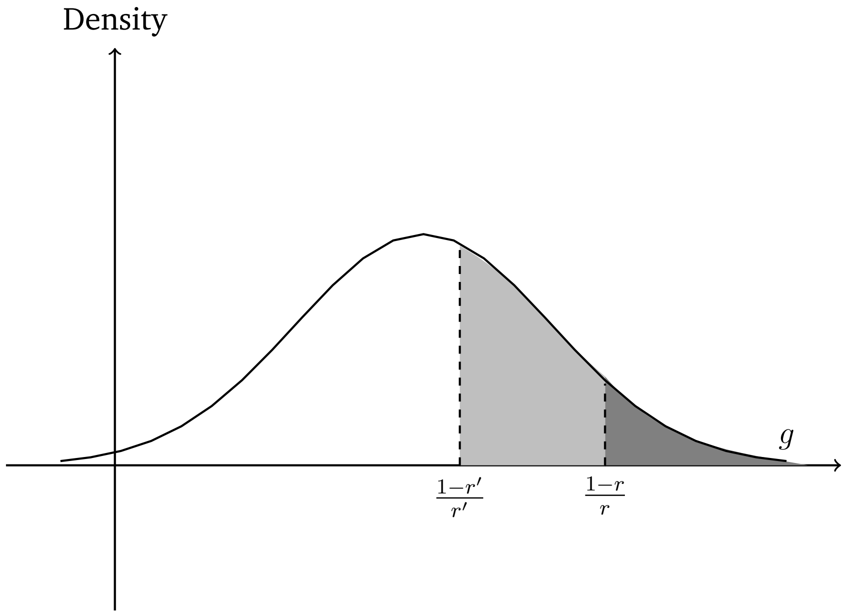
Finally, we make a prediction about the effect of changing the rate of return to public good contributions r. The higher r, the lower the cost of reducing guilt. Thus, when we increase r more people will match their contribution to the disclosed group expectations. Figure 3 shows an example where g_i 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 the rate of return is r. This is represented by the dark grey area in the figure. Suppose now we switch to a higher rate of return $r' > r$. As $\frac{1-r}{r} > \frac{1-r'}{r'}$, the fraction of players who match group expectations – given by the sum of the light grey and the dark grey areas – is larger than it was under rate of return r. This motivates our final prediction.

Prediction 3. *Players in a session assigned to $r = 4/5$ are more likely to choose contributions c_i^z that are equal to $\bar{\alpha}^z$ than players in a session assigned to $r = 3/5$.*

[14] In a recent theoretical paper, Attanasi et al. (2015) model a setting where players in a trust game have incomplete information about the guilt sensitivity of others. In our case, on the other hand, uncertainty is about the expectations of other players.

[15] Public disclosure may also increase the saliency of other people's expectations, raising the weight g_i attached to guilt.

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



4 Data and procedures

We conducted the field experiment in villages randomly sampled from four 'talukas' (sub-districts) of the Indian state of Maharashtra, between January and February 2014. We selected participants through door-to-door random sampling of male adult farmers. We completed 49 sessions with 381 subjects: 24 sessions of T-ND and and 25 sessions of T-D. Table 1 reports further information about sessions and participants. We invited eight subjects to each session of the experiment. In five sessions, however, we played the game with seven participants and in three sessions with six participants, as some farmers left after the beginning of the explanations.[16] We show in the balance analysis that the number of individuals per session is not correlated with treatment.

At the end of the game, participants compile a short questionnaire on their social and economic status. We summarise this data in Table 2 below.[17] Average age is 37 years. 78 percent of participant do not belong to a scheduled caste, tribe or an 'other backward caste' (OBC), 33 percent of them have completed high school. We also find that average total land holdings are about 4 hectares and average land cultivated is 3.2 hectares. On average, farmers report sharing information about agriculture on a regular basis with 6.8 other farmers.

The farmers who take part in the experiment know each other well. In the questionnaire we ask each subject about his interactions in the previous 30 days with each of the

[16]In most cases, famers who left did so early on in the experiment, before actual decisions were made. When the game was played with seven or six participants none of the rules were changed. In these sessions, the contribution of the centre player reached one or two individuals less.

[17]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 2. The variable 'information network size' is Winsorized at the 95th percentile of the distribution to exclude a few improbably high values.

Table 1: Number of observations by treatment

Treatment	Rate of return	Sessions	Players
T-ND	high	11	86
T-ND	low	13	101
All T-ND sessions		24	187
T-D	high	12	92
T-D	low	13	102
All T-D sessions		25	194
Total		49	381

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Age	36.817	10.459	20	75	378
Completed High School	0.331	0.471	0	1	375
Not scheduled caste or tribe	0.778	0.416	0	1	365
Land Owned	4.002	5.469	0	68	381
Land Cultivated	3.192	4.846	0	68	377
Information network size	6.719	4.615	0	20	367
Oneness	6.019	1.566	1	7	369

other participants in the session. 62 percent of farmers have spoken with all the other farmers and, on average, a farmer has spoken with 6 of the other 7 farmers. We also collect a measure of 'oneness' with the other participants. Social psychologists define the feeling of oneness 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). To measure this feeling we use the same visual scale developed by Aron et al. (1992) and deployed in the subsequent literature in social psychology. We report this items in Figure A.1 in the appendix. 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.

We translate the experimental instructions into Marathi, as Marathi is the most widely understood language in the areas of our study. The instructions are then translated back into English, to check the quality of the original translation.

We measure participants' understanding of the rules of the game by asking a series of questions before the experiment starts. These questions measure subjects' understanding of the network map, their ability to calculate payoffs, their awareness of the incentives

Table 3: Summary statistics: Session networks

Variable	Mean	Std. Dev.	Min.	Max.	N
Farmers with whom i has spoken	6.07	1.66	0	7	363
Average number of days spoken	7.81	7.14	1	30	352

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 during which the farmers spoke with each other, conditional on speaking on a strictly positive number of days.

created by the payoff rule, and their understanding of the strategy method. Figure A.2 in the appendix reports the cumulative distribution of mistakes in these questions. In the results sections, we show that our findings are robust to dropping players who make more than two mistakes in the understanding questions. Following the understanding test, enumerators disclose the right answers to the questions and give further instructions if necessary. Hence the understanding level reported in Figure A.2 is a lower bound of the actual understanding of players at the time of play. To further reinforce participants' understanding of the game, participants play a trial round of the game before actual play. The trial round features steps 1 and 4 in Figure 2, but does not include expectation elicitation or disclosure of group expectations. At the end of this trial round, the enumerator assigns temporary positions in the network with a random draw and informs participants of the payoff that they would earn given their decisions and position.

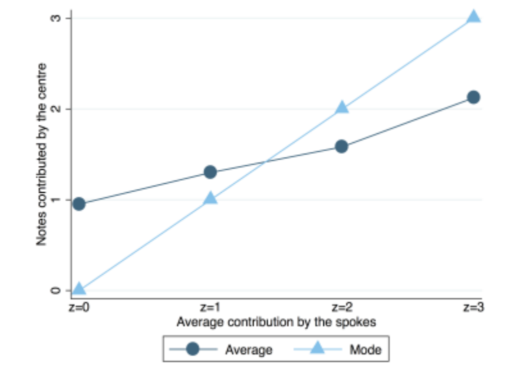
In Table A.1 in the appendix we present a set of regressions that test for covariate balance across treatments. We cannot find any statistically significant differences in the characteristics of players across treatments. We are also unable to find significant differences across treatments in the number of mistakes made in the understanding questions, nor in the number of individuals who leave the experiment before the end of the game.

5 Results

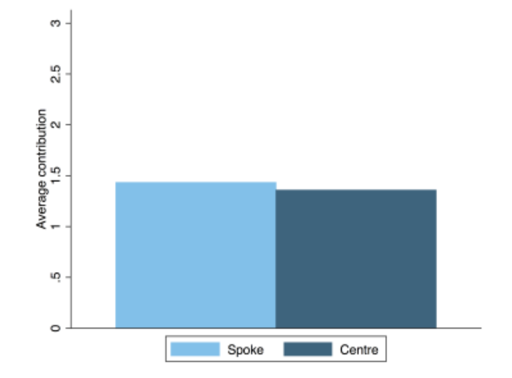
5.1 Contributions when playing as centre of the star

Our first finding is that players contribute equally to the public good when they are assigned to the spoke position as when they are placed at the centre of the star network. This is surprising in the light of the considerations of relative efficiency and equality that would motivate higher contributions from the centre of the star. In Figure 4a we aggregate the profiles of the star centres and plot the average and modal public good investments by spoke contribution level. The modal centre contribution is always equal to the average of the spokes. The average centre contribution is also close to the contribution of the spokes, in particular for $z = 1$ and $z = 2$. In other words, strict conditional cooperation is the modal behavior. Further, in Figure 4b we show the contributions that players would make if they are assigned to the spoke position, or if they are assigned to

Figure 4: Contributions to the public good in T-ND



(a) Contribution profiles



(b) Contributions

the centre position.[18] A signed-rank test cannot reject the null hypothesis that players choose equal contributions for the two positions (Z=.88, p=.38). On average, players contribute about half the endowment irrespective of their position in the network. In Figures A.7 and A.8 in the Appendix, we show that this result holds if we exclude centre contribution decisions for $z = 3$, which are most likely to suffer from censoring, or if we restrict the analysis to the subjects who have performed best in the initial understanding test (defined as making at most two mistakes in the test).

Result 1. *Players contribute on average half of their endowment to the public good, irrespective of their position in the network.*

We then investigate the shape of players' contribution profiles using regression analysis. We find that the average contribution profile has a slope below one and an intercept that is indistinguishable from zero. To obtain this result, we pool the four decisions in the profile of each player and create a small panel with four observations per player. We assume that a profile takes the following linear form:

$$c^*_{ijz} = \kappa + \beta z + u_{ijz} \tag{4}$$

where c^*_{ijz} captures the contribution that player i in session j wants to make if he is assigned to the centre position and the spokes contribute on average z. The intercept κ measures the contribution of the central player when the spokes contribute zero, while β captures the increase in central player contributions when the contribution of the spokes increases by one unit. If a player plays strict conditional cooperation, his profile will have $\kappa = 0$ and $\beta = 1$. Players may choose profiles characterised by other values of κ and β. However, as they are endowed with only three notes, their contributions are constrained to be in the interval between 0 and 3:

$$c_{ijz} = \min\left(\max(0, c^*_{ijz}), 3\right) \tag{5}$$

[18]For the centre position, we select for each individual the element from the contribution profile c_i that corresponds to the average spoke contribution in the session.

In our data corner solutions at both 0 and 3 occur frequently. We hence estimate the values of κ and β 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 $\beta = 1$ and study the direction of any deviation. To separately analyse the intercept and slopes for the T-ND treatment, we introduce a dummy for being in a T-D treatment and an interaction term capturing any additional effect of z in T-D sessions:

$$c^*_{ijz} = \kappa + \beta z + \gamma_1 \text{T-D}_j + \gamma_2(\text{T-D}_j * z) + u_{ijz} \tag{6}$$

In model (6), κ and β identify the intercept and slope of profiles in T-ND sessions. To perform inference, we correct standard error for clustering at the session level. We apply this correction to all regressions reported in the paper.

Columns 1 and 2 of Table 4 report results from the tobit regression. The point estimate of coefficient β is 0.75 (0.77 when controls are included) and is precisely measured. A Wald test indicates that this coefficient is significantly lower than one. The coefficient on the intercept κ has a point estimate of 0.32, which is statistically indistinguishable from 0. Thus, on average, the centre contributes as much as the spokes when the spokes contribute 0. As the average contribution of the spokes grows, the centre of the star increases his contributions by a factor of less than 1.

We provide four robustness checks. First, in columns 3 and 4 of Table 4 we report estimates from an ordered logit model of contributions. Point estimates as well as significance levels are very close to those of the tobit model. Second, we run a probit regression to estimate the effect of z on the likelihood that the dependent variable is at a corner solution. The tobit model assumes that z has 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 not at the corner. If this assumption holds, we would expect to find that the coefficients on z in the probit and tobit models have the same sign and comparable magnitude.[19] Table A.4 in the appendix shows that this is case. Third, we re-estimate the tobit and ordered logit models excluding centre contributions for $z = 3$, as these are likely to be the decisions most susceptible to censoring. Table A.5 in the Appendix shows that the results from this exercise are qualitatively very similar to those of Table 4. Lastly, in columns 3, 4, 7 and 8 of Table 4, we show that these results are not an artefact of poor understanding of the experimental design. For this purpose, we re-estimate the two regression models using only the decisions of subjects who have made at most two mistakes in the initial understanding test. The slope of the contribution profile that we estimate is now statistically indistinguishable from one, and the other results are qualitatively unchanged. We summarise these findings in the following result:

Result 2. *When playing as the centre of the star, subjects choose profiles where contributions track closely, but do not exceed the contributions of the spokes.*

[19] We apply both a lower and an upper limit. To study the effect of z on the upper limit, we analyse the probability that $c_i^z = 3$. To study the effect of z on the lower limit, we analyze the probability that $c_i^z > 0$. In both cases, we expect a positive coefficient, similar in magnitude to those reported in Table 4.

Table 4: The contribution profile of the centre player

	Tobit				Ordered logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel a								
Spoke average	.755	.768	1.035	1.004	.793	.807	1.030	1.000
	(.113)***	(.111)***	(.115)***	(.115)***	(.125)***	(.123)***	(.120)***	(.121)***
T-D	.204	.243	.139	.247	.244	.297	.234	.329
	(.302)	(.308)	(.402)	(.391)	(.292)	(.297)	(.363)	(.365)
T-D*Spoke average	-.096	-.099	-.200	-.211	-.124	-.137	-.226	-.230
	(.145)	(.148)	(.163)	(.165)	(.143)	(.145)	(.153)	(.158)
Const.	.323	-.201	-.231	-.723				
	(.230)	(.482)	(.333)	(.726)				
Panel b								
Spoke average = 1	4.73	4.39	.09	.00	2.76	2.46	.06	.00
	(.029)**	(.036)**	(.762)	(.971)	(.096)*	(.117)	(.799)	(.997)
Obs.	1524	1376	700	648	1524	1376	700	648
Subjects	All	All	High und.	High und.	All	All	High und.	High und.
Cluster N	49	49	49	49	49	49	49	49
Pseudo R^2	.047	.049	.074	.075	.06	.063	.093	.094
Log-likelihood	-2274.715	-2047.691	-1005.009	-930.503	-1985.11	-1787.302	-875.442	-811.115
Controls		✔		✔		✔		✔

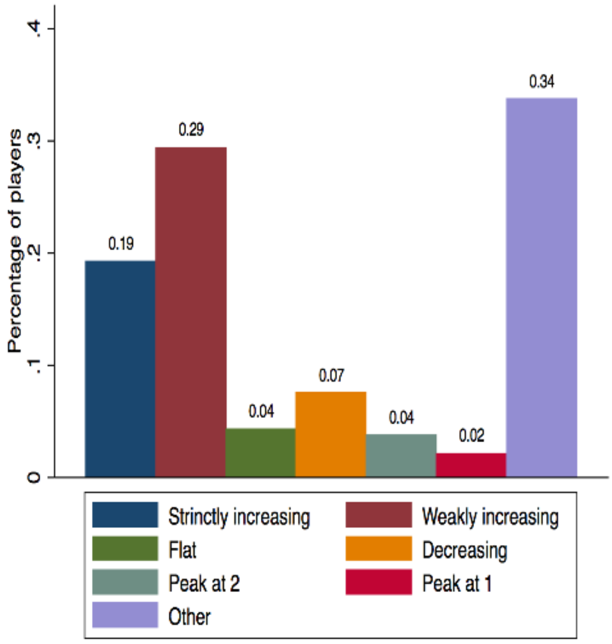
The dependent variable is the number of notes contributed to the public good by player i for 'centre contribution' decision z. The first four columns present a tobit regression, with an upper limit of 3 and a lower limit of 0. The last four columns present an ordered logit regression. Columns 3, 4, 7 and 8 only include observations for subjects who have made at most two mistakes in the understanding test. Columns 2, 4, 6 and 8 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper 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 two-sided Wald test on estimated coefficient $\hat{\beta}_1$.

In terms of the frequency with which particular profiles are chosen, we find that 48 percent of players select a profile consistent with conditional cooperation. The most popular contribution profile – $(0, 1, 2, 3)$ – exactly matches the average contribution of the spokes. Other popular profiles, like $(0, 0, 1, 3)$ and $(0, 1, 2, 2)$, specify contributions that are both *weakly increasing* in the average contribution of the spokes and *weakly lower* than the spoke average. The profile $(0, 3, 3, 3)$ was chosen by only 1.6 percent of players. Table A.2 in the appendix reports the most popular profiles and Figure 5 shows these profiles aggregated in the following 'archetypal' categories:

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 profiles appear not to be anchored on the spoke contribution decision. This is shown in table A.3 in the appendix. Only 2.5 percent of subjects specify a profile where the centre contribution is always equal to the contribution they would make if they played as spokes. Profiles where centre contributions equal the spoke contribution in three out of four cases are also rare (about 5 percent of all profiles).

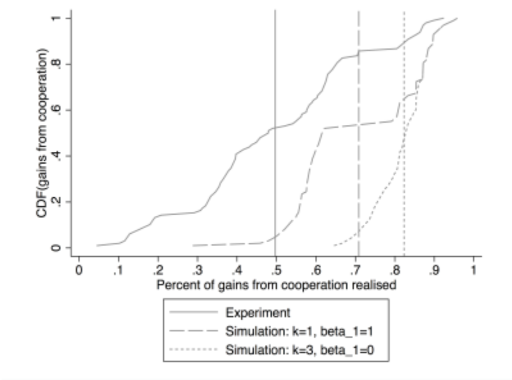
Figure 5: Archetypal contribution profiles in T-ND



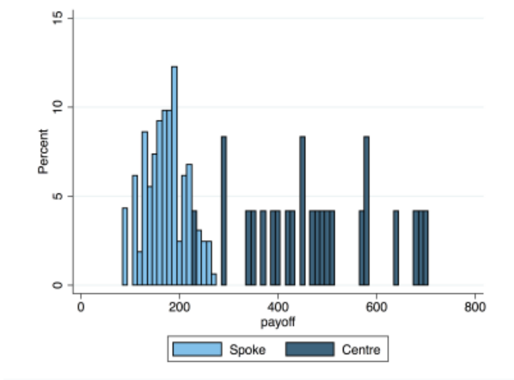
The strategies chosen by the centre of the star have strong repercussions on efficiency and payoff equality. In terms of efficiency, we find that players capture only about 50 percent of the 'potential gains from cooperation'.[20] This could be improved greatly by the actions of the central player alone, as we show in Figure 6. The left panel of Figure 6 plots the cumulative distribution function of the potential gains from cooperation that have been realised in the experiment, against the CDFs of two simulated distributions. In the two simulations, we hold the spoke contributions constant and change the centre contribution profile to either (i) $\kappa = 1$, $\beta = 1$, or (ii) $\kappa = 3$, $\beta = 0$. The vertical lines indicate the averages of the three distributions. Profile (i) is that of a strict conditional cooperator plus a positive shock of one to the intercept. If all centres of the star would choose this profile, players would capture 70 percent of the potential gains from cooperation. Profile (ii) is a flat profile where the centre of the star always contributes the maximum amount. If all centres of the star would choose this profile, players would capture on average 82

[20]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 and 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 $\Pi_{j|r}$ be the sum of individual payoffs in session j with a rate of return of r. $\frac{\Pi_{j|r} - \Pi(0)}{\Pi(3,r) - \Pi(0)}$ indicates the fraction of the potential gains from cooperation that is realised in session j.

Figure 6: Efficiency and equality



(a) Efficiency



(b) Equality

percent of the potential gains from cooperation. These results confirm the important role of the centre player in generating social welfare.

Conditional cooperation on part of the centre of the star also determines very high differences in payoff with the spoke players. The right hand side panel of Figure 6 shows a histogram of player payoffs, distinguishing between players who, at the end of the experiment, are assigned to the spoke position and players who are assigned to the centre position. On average, the centre player earns a monetary payment that is 200 percent higher than that of the spokes. This difference could be halved if the centre of the star contributed the maximum amount of three notes for every possible spoke average contribution level.

Result 3. *If the players at the centre of the star would always contribute the maximum amount to the public good, the participants would capture 82 percent of the potential gains from cooperation and payoff differences between spoke and centre players would be halved.*

5.2 Can we motivate players by disclosing group expectations?

In this section, we study the effects of disclosing group expectations on players's contribution decisions as centre of the star. We first investigate whether contributions that match group expectations become more frequent and then test whether the level of contributions changes.

5.2.1 The frequency of contributions that match group expectations

Our first finding is that, when we disclose group expectations, the frequency of contribution decisions that exactly match group expectations increases significantly. To show this, we pool data from T-ND and T-D and run a linear probability model of the following form:

$$\text{match}\left(c_{ij}^{z} = \bar{\alpha}_{j}^{z}\right) = \delta_0 + \delta_1 \text{T-D}_j + \delta_2 \text{High rate of return}_j + \delta_3\left(\text{T-D}_j * \text{High rate of return}_j\right) + e_{ijz} \quad (7)$$

Matches between contributions and group expectations are 11.5 percentage points more likely in T-D than in T-ND, as shown in Table 5. The effect is significant at the 5 percent level and corresponds to a 41 percent increase over the frequency of contributions that match group expectations in T-ND. When we add control variables, the magnitude of the coefficient increases slightly, and the effect becomes significant at the 1 percent level. We estimate similar coefficients on the T-D dummy if we exclude centre contribution decisions for $z = 3$ or we restrict the sample to the subjects with the best understanding (see Tables A.6 and A.7 in the Appendix). In Table A.8 in the Appendix we also show that expectation disclosure reduces the absolute difference between contributions and group expectations by a significant .14 notes, or .2 of a standard deviation. Overall, these results confirm our first prediction.

Result 4. *Contribution decisions that exactly match group expectations are significantly more likely in T-D compared to T-ND.*

We also find that the frequency of matches between contributions and expectations increases by a significant 11.3 percentage points when we raise the rate of return to investing in the public good. This confirms our third prediction. We show in Figure A.3 in the appendix that the larger part of this effect (66 percent) comes from a reduction in the frequency of decisions where $c_i^z < \bar{\alpha}^z$. This is also consistent with our theoretical framework, as the extra matches are predicted to come from individuals who find it too costly to reduce guilt when r is low.

Finally, we present evidence ruling out that the effects reported in this section are driven by underlying changes in the frequency of matches between contributions and *individual* expectations. For this purpose, we restrict the sample to cases in which individual and group expectations differ and check whether matches between contributions and *individual* expectations increase in T-D. We are unable to find evidence that this is the case, as shown in columns 5 and 6 of Table 5. Restricting the sample in the same way, on the other hand, does not change our estimate of the effect of expectations disclosure on the frequency of matches between contributions and group expectations (columns 3 and 4 of Table 5).

5.2.2 The level of contributions

We next show that the level of contributions is not significantly affected by the disclosure of expectations. For this purpose, we pool all contribution decisions together and regress the number of notes contributed on a dummy that identifies T-D sessions:

$$c_{ijz} = \eta_0 + \eta_1 \text{T-D}_j + u_{ijz} \quad (8)$$

Table 5: Do contributions in T-D match group expectations more often than in T-ND?

	Contribution = Group expectation				Contribution = Individual expectation	
	(1)	(2)	(3)	(4)	(5)	(6)
T-D	.115 (.046)**	.122 (.045)***	.121 (.045)***	.126 (.051)**	.001 (.063)	.002 (.063)
High rate of return	.113 (.035)***	.123 (.039)***	.060 (.035)*	.075 (.041)*	.038 (.055)	.034 (.056)
T-D * High rate of return	-.054 (.069)	-.067 (.072)	-.032 (.065)	-.040 (.076)	.007 (.079)	-.027 (.089)
Const.	.282 (.015)***	.337 (.086)***	.183 (.024)***	.268 (.111)**	.471 (.049)***	.557 (.135)***
Obs.	1524	1376	922	830	922	830
Sample	Full	Full	Restricted	Restricted	Restricted	Restricted
Cluster N	49	49	49	49	49	49
Controls		✔		✔		✔

OLS regression. In columns 1-4 the dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha}^z$. In columns 5 and 6 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 in the session $r = \frac{4}{5}$. Columns 2, 4 and 6 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

We find that subjects in T-D contribute .025 notes more than subjects in T-ND. This coefficient is very small – average contributions are about 1.5 notes – and, as shown in Table 6, not significantly different from zero. We find qualitatively similar results if we exclude players who have made more than two mistakes in the understanding test (columns 3 and 4) or if exclude centre contribution decisions for $z = 3$ (see Table A.9 in the Appendix).

Result 5. *The level of centre contributions in T-D is not significantly different from the level of centre contributions in T-ND.*

Why are contribution levels unchanged? To answer this question we turn to the data on players' expectations and report two findings. First, individuals do not generally expect the centre of the star to exceed the contributions of the spokes. To establish this, we estimate model (6) with expectations α_i^z as the dependent variable. The coefficient β now measures the extent to which players *expect* others to increase their centre of the star contributions when the spoke contributions increase. Table A.10 in the appendix reports the coefficient estimates: β is about 0.65 and is significantly smaller than 1, while κ is positive and significant in the regression without controls, but negative and insignificant once we include controls. Further, Figure A.4 in the Appendix shows that the modal expected contribution from the centre player is equal to the spoke contribution. These results suggest that subjects expect the central player to be a conditional cooperator. This is confirmed by an investigation of the individual expectation profiles (Table A.11 and Figure A.5 in the appendix).

Second, the group expectations that are implied by these individual beliefs are very

Table 6: Does expectation disclosure change the level of contributions?

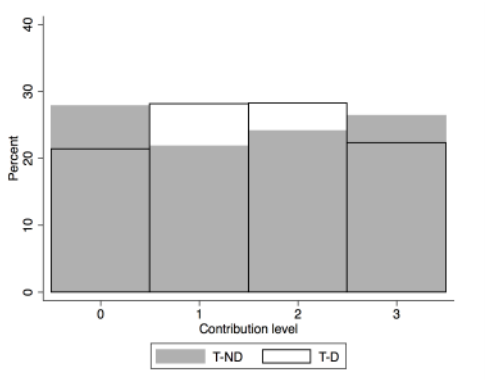
	(1)	(2)	(3)	(4)
T-D	.025	.044	-.087	-.040
	(.080)	(.083)	(.130)	(.136)
Const.	1.489	1.225	1.422	1.141
	(.067)***	(.223)***	(.116)***	(.318)***
Obs.	1524	1376	700	648
Subjects	All	All	High understanding	High understanding
Cluster N	49	49	49	49
Controls		✔		✔

OLS regression. The dependent variable is the number of notes contributed to the public good. Columns 3 and 4 only include observations for subjects who have made at most two mistakes in the understanding test. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

often either one or two notes (see Table A.12 in the Appendix[21]). Consistently with this, we show in Figure 7 that contributions of one or two notes become more frequent in T-D compared to T-ND. Further, *both* contributions of zero notes and contributions of three notes become less frequent, suggesting that the number of individuals who overestimated what other players expect from the centre of the star is similar to the number of those who underestimated it. In T-D the misperceptions of both types of individuals are corrected, leading those who overestimated (underestimated) group expectations to decrease (increase) their contributions to the public good. The net effect on contributions is close to zero.

Finally, it is important to note that in the T-D treatment some players contribute above the group expectations that we disclose (see Figure 7 and Figure A.3 in the Appendix). This suggests that these players have motives other than guilt aversion to contribute to the public good, for example a preference for efficiency.

Figure 7: Centre player contributions in T-ND and T-D



[21]The figures reported in Table A.12 have been rounded to the nearest integer. Thus, a session where, say, $\bar{\alpha}^z = 0.55$ has a rounded value of group expectations of 1.

5.3 Heterogeneity

In this section, we leverage the data on the connections between the participants of the experiment. We are interested to explore heterogeneity along two dimensions: individual measures of network position and session-level measures that describe the structure of the network that connects the participants.

5.3.1 Individual position in the network

We begin by studying whether individuals who have a central position in social networks outside of the experiment make different decisions when playing as centre players in the public good game. We use two different measures of centrality: (i) the number of farmers with whom an individual regularly exchanges information about agriculture, and (ii) the number of other farmers in the session with whom the individual has spoken in the last 30 days. We call the first variable 'degree' and the second variable 'session degree'. For comparison, we also study whether decisions are related to the amount of land owned by the player, an indicator of wealth, or by the self-reported level of oneness with the group, and indicator of psychological closeness with others. For each of these variables, we calculate a dummy x_{ij} which captures whether player i is above the median level of that variable. We then run the following two models:

$$c_{ijz}^{*} = \kappa + \beta z + \phi_1 x_{ij} + \phi_2 (z * x_{ij}) + u_{ijz} \tag{9}$$

$$\begin{aligned} \text{match}\left(c_{ij}^{z} = \bar{\alpha}_{j}^{z}\right) = \delta_0 + \phi x_i + \delta_1 \text{T-D}_j + \delta_2 \text{High rate of return}_j \\ + \delta_3 \left(\text{T-D}_j * \text{High rate of return}_j\right) + e_{ijz} \end{aligned} \tag{10}$$

We are unable to find any statistically significant evidence suggesting that individuals who have a central position in farmer networks make different decisions in the public good game. We also do not find any evidence showing that central farmers are more responsive to the expectations of others. We report these results in Tables A.13 and A.14.

5.3.2 Network structure

We then turn to the structure of the connections between participants. We are interested to capture both the density and the intensity of social links. To do this, we compute session-level averages of the following variables: (i) the number of players in the session with whom each subject has spoken in the last 30 days (to measure density)[22] and (ii) the average number of days, in the previous 30 days, on which a subject has spoken with the other participants (to measure intensity)[23]. As before, we split continuous variables at the median and create a dummy x_j capturing whether a session has a level of the variable above the median. We then estimate a model of this type:

[22]This is the variable 'session degree', which we used at the individual level in the previous section.

[23]We compute this average considering only partners with whom the subject has spoken on a positive number of days.

Table 7: Contributions and session-level characteristics

	(1)	(2)
T-D	.179	.127
	(.085)**	(.102)
High intensity	.283	
	(.121)**	
T-D * High intensity	-.310	
	(.150)**	
High density		.080
		(.128)
T-D * High density		-.222
		(.154)
Const.	1.350	1.443
	(.061)***	(.084)***
Obs.	1524	1524
Cluster N	49	49

OLS regression. The dependent variable is the number of notes contributed to the public good. Confidence: *** ↔ 99%, ** ↔ 95%, * ↔ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

$$c_{ijz} = \gamma_0 + \gamma_1 \text{T-D}_j + \gamma_2 x_j + \gamma_3 \left(\text{T-D}_j * x_j\right) + u_{ijz} \tag{11}$$

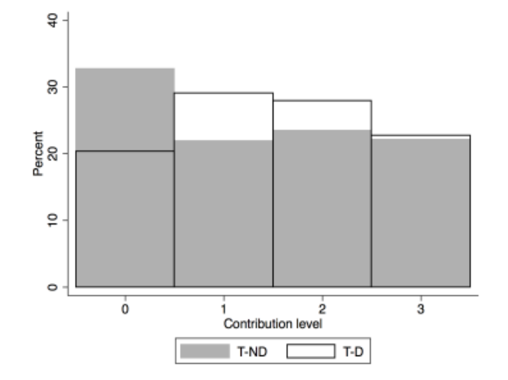
We show in Table 7 that when networks have low intensity, disclosure of expectations increases contributions by about .18 notes – 13% of the control mean – an effect significant at the 5 percent level. Further, disclosing expectation is significantly less effective in high intensity sections. For density, we find similar, but smaller and insignificant effects.

Result 6. *In networks where participants are not strongly connected to each other, disclosing expectations increases contributions by a significant 13%.*

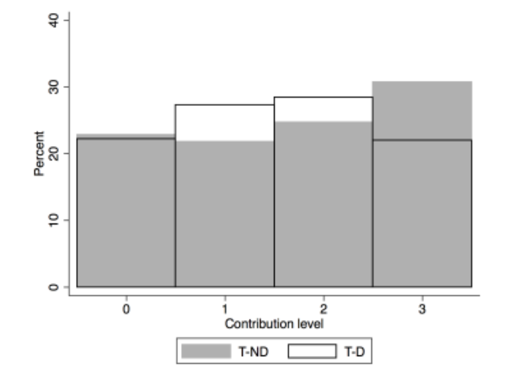
Why is disclosing expectations particularly effective in networks where participants are not strongly connected to each other? We show in Figure 8 that, when individuals are connected by relatively weak links, the most frequent contribution decision is zero. Disclosing expectations reduces the share of zero contributions by more than 10 percentage points. Conversely, when individuals are connected by strong links, the most frequent contribution decision is three and this too is decreased by the disclosure of expectations.

These patterns suggests that in groups where connections are weak, individuals are more likely to underestimate what other people expect from high influence players. In groups where connections are strong, on the other hand, individuals overestimate what others expect. We corroborate this interpretation by studying, in Figure A.6 in the appendix, the frequency of contribution decisions that match group expectations in low and high intensity networks. We find that in both types of networks disclosing expectations increases the frequency of contribution decisions that match group expectation. However, in low intensity networks, this happens mostly by reducing the proportion of contributions that are below group expectations, while in high intensity networks, the effect comes mostly from a reduction in contributions that are above group expectations.

Figure 8: Centre player contribution in low and high intensity networks



(a) Low intensity



(b) High intensity

6 Conclusion

In this paper, we study a one-shot public good game where subjects are connected by a star network with one centre player and seven spokes. We find that, when they are in the centre position, subjects contribute as much as the average contribution of the spokes. This strategy, known as 'conditional cooperation', has frequently been observed in standard public good games. A key contribution of this study is to show that subjects play conditional cooperation even when both efficiency and equality would require the star centre to contribute more than the rest. We also show that the expectations of other people can be a powerful motivator in this context, confirming the predictions of a simple model of guilt aversion. Lastly, we document that, when participants have weak social ties to each other, disclosing group expectations significantly increases the public good contributions that star centres make. Overall, this constitutes some of the first evidence for guilt aversion outside of Western populations. Further, the heterogeneity of results with respect to social ties highlights the importance of having access to sufficient variation in the characteristics of experimental subjects (Charness et al., 2013).

These findings have implications for policy. First, government interventions often select particular individuals who are then – implicitly or explicitly – required to unilaterally take a costly action for the benefits of others. Examples of such interventions include: agricultural extension programmes that rely on 'model farmers'; the dissemination of health information through locally trained agents; and many forms of viral marketing (Ben Yishay and Mobarak, 2012; Berg et al., 2013; Kondylis et al., 2017). Our results suggest that it would be unwise to expect that the individuals selected in these interventions, who have been endowed with the capacity to generate large benefits for others, will in fact generate these benefits unilaterally. The dominant behaviour is to match the contribution of others.

Second, our results illustrate both the potential and the limits of providing information about the expectations of others as a mechanism for increasing contributions to the public good. Guilt aversion can in principle be used to incentivize people in positions of influence, for instance by holding public meetings that indirectly reveal other people's expectations towards them. However, doing so only increases the contributions of leaders when they initially underestimated group expectations. The evidence suggests this is more likely to be the case in networks characterised by relatively weak connections. This raises the question of how individuals form beliefs about the expectations of others. Answering this question is important because, when individuals are motivated to meet these expectations, institutions that generate low priors about the expectations of others can lead groups to fall into a low pro-sociality 'trap'. In general we do not know enough about the process through which individuals form these beliefs. More research is needed on this issue.

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A.1 The contribution profile under different models of social preferences

A.1.1 Fehr and Schmidt 1999

We consider a player i at the centre of the star with inequality-averse preferences as defined in Fehr and Schmidt (1999). The player has to decide how much to contribute to the public good when the spokes have contributed on average z. His utility function is given by:

$$U_i(\boldsymbol{\pi}) = \pi_i - \alpha_i \frac{1}{n-1} \sum_{j \neq i}^{n} \max[\pi_j - \pi_i, 0] - \beta_i \frac{1}{n-1} \sum_{j \neq i}^{n} \max[\pi_i - \pi_j, 0] \tag{A.1}$$

This player cares about his person payoff π_i and dislikes payoff distributions where he earns more than the spokes or where the spokes earn more than him. We assume that the player is sufficiently inequality averse, in the sense that $\alpha_i > 0$ and $\beta_i > 1 - r$. As the players does not know whether there is any variation in spoke contributions around the average z, we assume that the player believes each spoke has contributed exactly z and earns the same payoff π_j. The utility function thus becomes:

$$U_i(\boldsymbol{\pi}) = \pi_i - \alpha_i \max[\pi_j - \pi_i, 0] - \beta_i \max[\pi_i - \pi_j, 0]$$

We now show that the optimal contribution profile for this player is $(0, 3, 3, 3)$. Let us normalise the value of each note to 1. The payoff of the centre of the star is given by: $\pi_i = 3 - (1-r)c_i^z + 7rz$. The payoff of a spoke j is given by $\pi_j = 3 - (1-r)z + rc_i^z$, and the difference between the two is $\pi_i - \pi_j = (6r+1)z - c_i^z$. Thus the centre has a higher payoff than the spokes if $(6r+1)z > c_i^z$, and the spokes have a higher payoff if $(6r+1)z < c_i^z$. Our proof proceeds in two steps.

1. Consider the case where $z \in \{1, 2, 3\}$. In this case, as r is at least $3/5$, $\pi_i > \pi_j$ irrespective of c_i^z. In other words, the centre can decrease but not erase advantageous inequality. The centre player utility is now given by:

$$\begin{aligned} U_i(\boldsymbol{\pi}) &= \pi_i - \beta_i(\pi_i - \pi_j) \\ &= 3 - (1-r)c_i^z + 7rz - \beta_i\left((6r+1)z - c_i^z\right) \\ &= 3 + (\beta_i - (1-r))c_i^z + \left(7r - \beta_i\,(6r+1)\right) z. \end{aligned}$$

As $\beta_i > (1-r)$, utility monotonically increases with contributions and is maximised by choosing the maximum amount of contributions: $c_i^z = 3$.

2. Consider the case where $z = 0$. The difference between spoke and centre payoff is now given by $\pi_j - \pi_i = c_i^0$, which implies the spoke payoff is weakly greater than the payoff of the centre. In this case, the centre player utility is given by:

$$\begin{aligned} U_i(\boldsymbol{\pi}) &= \pi_i - \alpha_i(\pi_j - \pi_i) \\ &= 3 - (1-r)c_i^0 - \alpha_i c_i^0. \end{aligned}$$

Utility now monotonically decreases with contributions and is maximised by setting $c_i^0 = 0$.

A.1.2 Bolton and Ockenfels 2000

We now turn to the concept of aversion to relative inequality proposed by Bolton and Ockenfels (2000). As in the previous subsection we consider the contribution choice of the centre player for four possible values of the average spoke contribution. Given this, for simplicity of exposition, we consider the following additively separable preference function:

$$U_i(\boldsymbol{\pi}) = \pi_i - \alpha_i \left(\sigma_i - \frac{1}{8}\right)^2 \tag{A.2}$$

where $\sigma_i = \frac{\pi_i}{\sum_{k=1}^{8} \pi_k}$ if $\sum_{k=1}^{8} \pi_k > 0$, and $\sigma_i = 1/8$ if $\sum_{k=1}^{8} \pi_k = 0$. As before it is immediately apparent that when $z = 0$ the utility of the centre player is maximized by setting $c_i^0 = 0$: not only does setting $c_i^0 > 0$ reduce π_i, it also increases inequality.

Now consider the case where $z = \{1, 2, 3\}$. The centre player utility is now given by:

$$\begin{aligned} U_i(\boldsymbol{\pi}) &= \pi_i - \alpha_i \left(\frac{\pi_i}{\pi_i + 7\pi_j} - \frac{1}{8}\right)^2 \\ &= \pi_i - \alpha_i \left(\frac{1}{1 + 7\frac{\pi_j}{\pi_i}} - \frac{1}{8}\right)^2 \end{aligned}$$

As before, when $z = \{1, 2, 3\}$, $\pi_i > \pi_j$ irrespective of the centre player contribution. This implies that $\frac{1}{1+7\frac{\pi_j}{\pi_i}} < \frac{1}{8}$. The centre player can increase the ratio $\frac{\pi_j}{\pi_i}$ by contributing more to the public good. Thus, for a large enough α_i, the star centre will always select the value of c_i^z that yields the largest possible value of $\frac{\pi_j}{\pi_i}$ i.e., he will set $c_i^z = 3$ for $z = \{1, 2, 3\}$. For intermediate levels of α_i, other profiles are also possible. This is due to the non-linear impact of relative inequality on utility in the model. For example, when $\alpha_i = 8.5$ and $r = \frac{3}{5}$, the optimal contribution profile is $\{0, 2, 3, 3\}$.

A.1.3 Charness and Rabin 2002

We now turn to the concept of inequality aversion proposed by Charness and Rabin (2002). The preferences of the centre of the star are now written:

$$U_i(\boldsymbol{\pi}) = (1 - \rho_i t - \sigma_i s - \theta_i q)\pi_i + (\rho_i t + \sigma_i s + \theta_i q)\pi_j \tag{A.3}$$

where $t = 1$ if $\pi_i > \pi_j$ and 0 otherwise, $s = 1$ if $\pi_i < \pi_j$ and 0 otherwise, and $q = -1$ if j has misbehaved and 0 otherwise. Further, as before, we assume that the centre believes that each spoke has contributed exactly z and thus earns the same payoff π_j. Parameters ρ_i and σ_i can be positive or negative, depending on preferences. Inequality aversion (or difference aversion as defined by Charness and Rabin) is captured by setting $\sigma_i < 0 < \rho_i < 1$, which we now assume. To focus only on inequality aversion, we also assume that $\theta_i = 0$, i.e., subjects do not have normative preferences regarding spokes' contributions.

Let us first consider the case where $z = 0$. If $c_i^0 = 0$, $\pi_j = \pi_i$ and thus $t = s = 0$. The value of the utility function is simply π_i. In contrast, for $c_i^0 > 0$, we have $\pi_i < \pi_j$ and thus $s = 1$ and $t = 0$. Utility is now given by:

$$U_i(\boldsymbol{\pi}) = (1 - \sigma_i)\pi_i + \sigma_i \pi_j$$
$$= \pi_i + \sigma_i(\pi_j - \pi_i).$$

This is strictly less than π_i as $\sigma_i < 0$ and $\pi_j > \pi_i$. It follows that $c_i^0 = 0$ is the optimal action for a player with preferences given by A.3.

Let us now consider the case where $z = \{1, 2, 3\}$. In this case, for any level of contribution by the centre of the star, $\pi_i > \pi_j$, and thus $t = 1$ and $s = 0$. Utility is now given by:

$$U_i(\boldsymbol{\pi}) = (1 - \rho_i)\pi_i + \rho_i \pi_j$$
$$= \pi_i - \rho_i(\pi_i - \pi_j)$$

This is resembles very closely the analysis for $z = \{1, 2, 3\}$ and Fehr and Schmidt preferences (the only difference is that the inequality aversion parameter is called ρ_i instead of β_i). Thus, as before, if $\rho_i > 1 - r$, $c_i^z = 3$ will be optimal for $z = \{1, 2, 3\}$.

A.2 Figures

Figure A.1: Oneness question

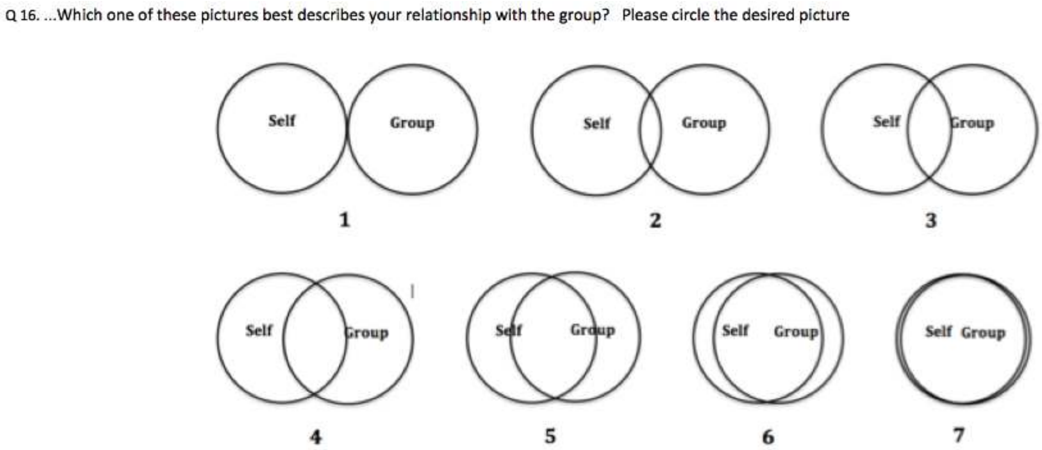


Figure A.2: Cumulative distribution of mistakes

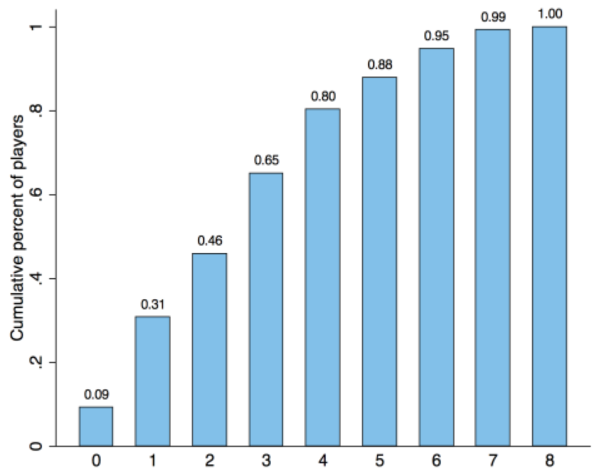


Figure A.3: Match between contribution and group expectations. T-D treatment.

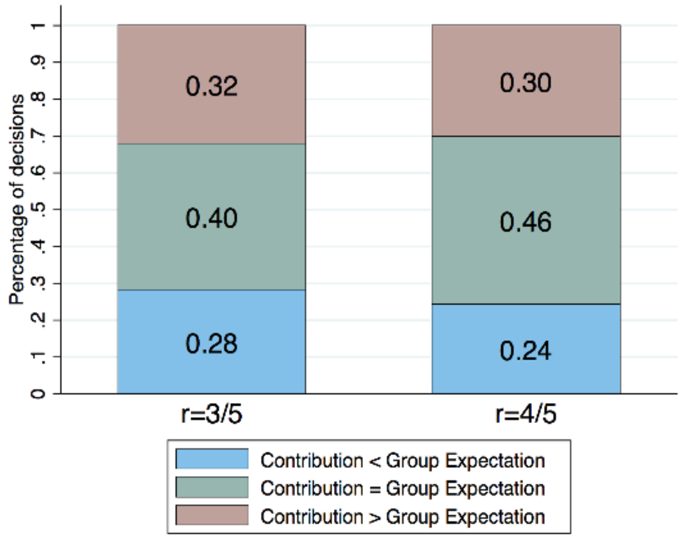


Figure A.4: Expectation profiles in T-ND

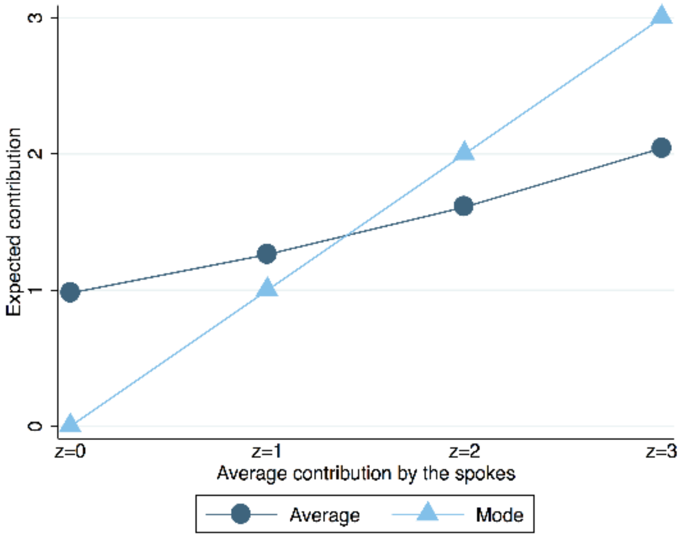


Figure A.5: Archetypal expectation profiles in T-ND

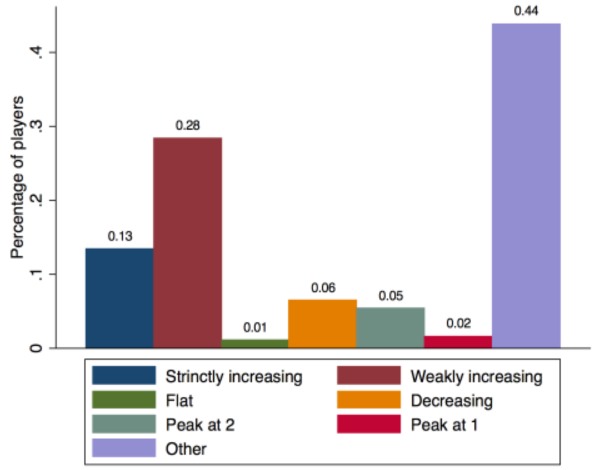
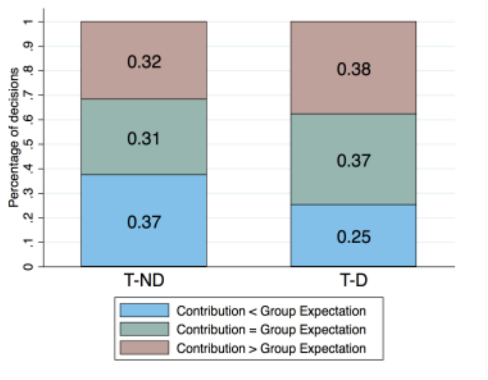
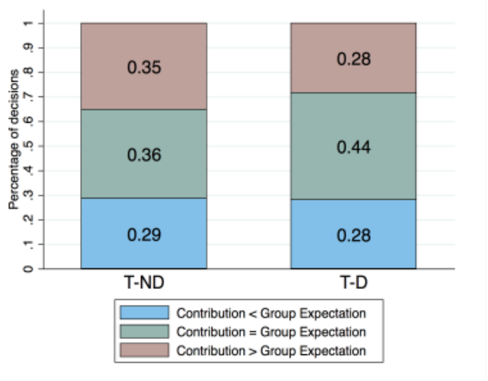


Figure A.6: Match between contributions and expectations in low and high intensity networks



(a) Low intensity



(b) High intensity

Figure A.7: Contributions to the public good in T-ND (Excluding centre contributions for $z = 3$).

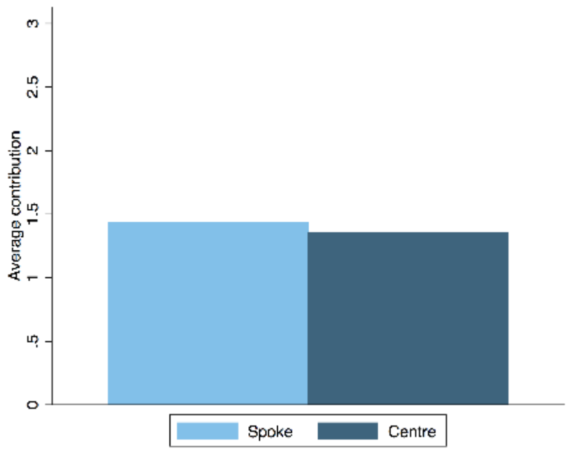
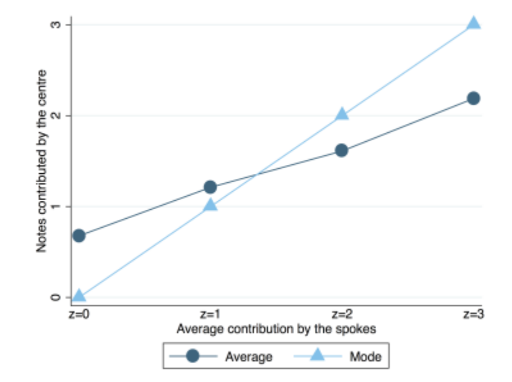
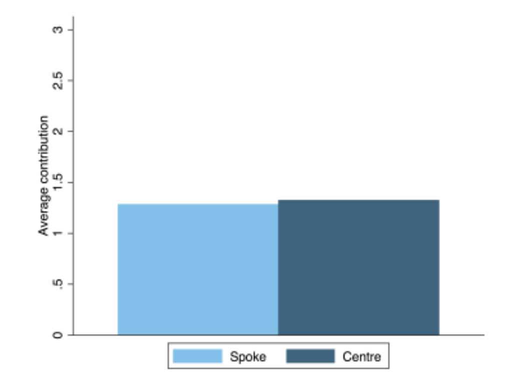


Figure A.8: Contributions to the public good in T-ND. High understanding players



(a) Contribution profiles



(b) Contributions

A.3 Tables

Table A.1: Balance test

	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
	(1.427)	(.072)	(.070)	(.600)	(.554)	(.709)	(.229)	(.254)	(.159)
Const.	37.123	.728	.341	4.402	3.283	7.039	6.106	2.818	7.792
	(1.049)***	(.055)***	(.050)***	(.508)***	(.440)***	(.485)***	(.149)***	(.190)***	(.120)***
Obs.	378	365	375	381	377	367	369	381	49

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. 'Degree' 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 A.2: Most frequently chosen contribution profiles in T-ND. 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

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 T-ND.

Table A.3: Do players anchor the centre contribution on the spoke contribution?

$\sum_{z=0}^{4} c_i^z = s_i$	Percentage
0	19.25
1	55.61
2	17.11
3	5.35
4	2.67

Data from T-ND.

Table A.4: Robustness of tobit assumption

	Dependent var: $c_i^z > 0$		Dependent var: $c_i^z = 3$	
	(1)	(2)	(3)	(4)
Spoke average	.450	.451	.263	.267
	(.065)***	(.065)***	(.059)***	(.057)***
T-D	.232	.248	-.103	-.089
	(.152)	(.159)	(.172)	(.176)
T-D * Spoke average	-.002	.001	-.019	-.015
	(.091)	(.095)	(.076)	(.077)
Const.	-.016	-.232	-1.052	-1.357
	(.107)	(.340)	(.121)***	(.249)***
Obs.	1524	1376	1524	1376
Cluster N	49	49	49	49
Pseudo R^2	.116	.127	.041	.044
Log-likelihood	-751.012	-668.857	-810.307	-736.547

Probit regression. The dependent variable is a dummy variable described in the heading of each column. Columns 2 and 4 restrict the analysis to players who have made at most two mistakes in the initial understanding questions. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table A.5: The contribution profile of the centre player (Excluding centre contributions for $z = 3$)

	Tobit		Ordered logit	
	(1)	(2)	(3)	(4)
Panel a				
Spoke average	.599	.590	.725	.723
	(.115)***	(.120)***	(.147)***	(.155)***
T-D	.084	.102	.144	.177
	(.298)	(.309)	(.325)	(.339)
T-D * Spoke average	.056	.089	.010	.039
	(.162)	(.172)	(.182)	(.194)
Const.	.471	-.277		
	(.217)**	(.514)		
Panel b				
Spoke average = 1	12.22	11.78	3.53	3.2
	(.001)***	(.001)***	(.06)*	(.074)*
Obs.	1143	1032	1143	1032
Cluster N	49	49	49	49
Pseudo R^2	.026	.032	.036	.044
Log-likelihood	-1728.528	-1551.97	-1502.468	-1347.93
Controls		✔		✔

The dependent variable is the number of notes contributed to the public good by player i for 'centre contribution' decision z. The first two columns present a tobit regression, with an upper limit of 3 and a lower limit of 0. The last two columns present an ordered logit regression. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper 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 two-sided Wald test on estimated coefficient $\hat{\beta}_1$.

Table A.6: Do contributions in T-D match group expectations more often than in T-ND? (Excluding centre contributions for $z = 3$)

	Contribution = Group expectation				Contribution = Individual expectation	
	(1)	(2)	(3)	(4)	(5)	(6)
T-D	.115	.119	.121	.126	.001	.002
	(.058)**	(.059)**	(.045)***	(.051)**	(.063)	(.063)
High rate of return	.082	.092	.060	.075	.038	.034
	(.042)*	(.047)*	(.035)*	(.041)*	(.055)	(.056)
T-D * High rate of return	-.023	-.041	-.032	-.040	.007	-.027
	(.078)	(.084)	(.065)	(.076)	(.079)	(.089)
Const.	.290	.345	.183	.268	.471	.557
	(.027)***	(.084)***	(.024)***	(.111)**	(.049)***	(.135)***
Obs.	1143	1032	922	830	922	830
Sample	Full	Full	Restricted	Restricted	Restricted	Restricted
Cluster N	49	49	49	49	49	49
Controls		✔		✔		✔

OLS regression. In columns 1-4 the dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha}^z$. In columns 5 and 6 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 in the session $r = \frac{4}{5}$. Columns 2, 4 and 6 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table A.7: Do contributions in T-D match group expectations more often than in T-ND? (High understanding subjects)

	Contribution = Group expectation				Contribution = Individual expectation	
	(1)	(2)	(3)	(4)	(5)	(6)
T-D	.102	.093	.107	.111	.068	.063
	(.078)	(.072)	(.065)*	(.064)*	(.087)	(.090)
High rate of return	.106	.103	-.008	.010	.123	.129
	(.051)**	(.056)*	(.058)	(.062)	(.071)*	(.080)
T-D * High rate of return	-.018	-.004	.059	.073	-.152	-.216
	(.106)	(.111)	(.108)	(.119)	(.137)	(.161)
Const.	.311	.409	.197	.328	.462	.322
	(.027)***	(.125)***	(.042)***	(.134)**	(.063)***	(.219)
Obs.	700	648	416	384	416	384
Sample	Full	Full	Restricted	Restricted	Restricted	Restricted
Cluster N	49	49	49	49	49	49
Controls		✔		✔		✔

OLS regression. Only observations from subjects who have made at most two mistakes in the understanding tests are included. In columns 1-4 the dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha}^z$. In columns 5 and 6 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 in the session $r = \frac{4}{5}$. Columns 2, 4 and 6 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table A.8: Absolute difference between contributions and group expectations

	Absolute difference	
	(1)	(2)
T-D	-.136	-.144
	(.069)**	(.071)**
High rate of return	-.136	-.148
	(.053)**	(.059)**
T-D * High rate of return	.040	.067
	(.097)	(.102)
Const.	.903	.682
	(.031)***	(.136)***
Obs.	1524	1376
Cluster N	49	49
Controls		✔

OLS regression. Columns 2 includes controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table A.9: Does expectation disclosure change the level of contributions? (Excluding centre contributions for $z = 3$)

	t1	t2
	(1)	(2)
T-D	.064	.094
	(.095)	(.098)
Const.	1.278	.846
	(.075)***	(.273)***
Obs.	1143	1032
Cluster N	49	49
Controls		✔

OLS regression. The dependent variable is the number of notes contributed to the public good. Column 2 includes controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper caste. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level are reported in parentheses.

Table A.10: Expectations about the contribution of the centre player

	Tobit		Ordered logit	
	(1)	(2)	(3)	(4)
Panel a				
Spoke average	.659	.637	.700	.679
	(.087)***	(.092)***	(.098)***	(.103)***
T-D	-.057	-.068	-.090	-.102
	(.247)	(.260)	(.250)	(.260)
T-D*Spoke average	.037	.084	.047	.093
	(.121)	(.127)	(.120)	(.126)
Const.	.445	-.449		
	(.171)***	(.412)		
Panel b				
Spoke average = 1	15.45	15.56	9.44	9.73
	(.000)***	(.000)***	(.002)***	(.002)***
Obs.	1524	1376	1524	1376
Cluster N	49	49	49	49
Pseudo R^2	.048	.052	.061	.065
Log-likelihood	-2274.73	-2044.976	-1980.611	-1781.251
Controls		✔		✔

The dependent variable is expectation α_i^z. The first two columns present a tobit regression, with an upper limit of 3 and a lower limit of 0. The last two columns present an ordered logit regression. Columns 2 and 4 include controls for the players' age, area of land owned, area of land cultivated, self-reported oneness with the group, and dummies for having completed secondary education, and for belonging to an upper 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 two-sided Wald test on estimated coefficient $\hat{\beta}_1$.

Table A.11: Most frequently chosen expectation profiles in T-ND. 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

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 A.12: Group expectations by spoke contribution

	Percentage of sessions where			
	$\bar{\alpha}^z = 0$	$\bar{\alpha}^z = 1$	$\bar{\alpha}^z = 2$	$\bar{\alpha}^z = 3$
$z = 0$	24	60	16	0
$z = 1$	0	76	24	0
$z = 2$	0	40	60	0
$z = 3$	0	16	68	16

Table A.13: Contributions and player characteristics

	Degree		Session degree		Oneness		Land owned	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Spoke average	.705 (.071)***	.697 (.103)***	.705 (.071)***	.750 (.085)***	.705 (.071)***	.736 (.121)***	.705 (.071)***	.824 (.105)***
Degree	-.077 (.121)	-.097 (.221)						
Degree * Spoke Average		.013 (.120)						
Session degree			.044 (.142)	.150 (.273)				
Session degree * spoke average				-.069 (.114)				
Oneness					-.024 (.100)	.052 (.250)		
Oneness * spoke average						-.050 (.138)		
Land owned							-.184 (.112)*	.168 (.222)
Land owned * spoke average								-.232 (.127)*
Const.	.477 (.154)***	.489 (.191)**	.400 (.167)**	.332 (.205)	.444 (.154)***	.397 (.223)*	.523 (.164)***	.344 (.208)*
Obs.	1524	1524	1524	1524	1524	1524	1524	1524
Cluster N	49	49	49	49	49	49	49	49
Pseudo R^2	.047	.047	.046	.047	.046	.046	.047	.048
Log-likelihood	-2275.133	-2275.125	-2275.318	-2275.068	-2275.378	-2275.242	-2273.761	-2270.689

Tobit regression, with an upper limit of 3 and a lower limit of 0. The dependent variable is contributions α_i^c. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level.

Table A.14: Match between contributions and expectations, and player characteristics

	Degree	Session degree	Oneness	Land owned
	(1)	(2)	(3)	(4)
Degree	.011 (.027)			
Session degree		.035 (.033)		
Oneness			-.029 (.027)	
Land owned				-.017 (.032)
Const.	.275 (.025)***	.261 (.025)***	.297 (.020)***	.292 (.020)***
Obs.	1524	1524	1524	1524
Cluster N	49	49	49	49

OLS regression. The dependent variable is a dummy variable that takes a value of 1 if $c_i^z = \bar{\alpha}^z$. Confidence: *** $\leftrightarrow$ 99%, ** $\leftrightarrow$ 95%, * $\leftrightarrow$ 90%. Standard errors corrected for clustering at session level.