One Bad Apple: Uncertainty and Heterogeneity in Public Good Provision

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Abstract:

Previous research has demonstrated that people are not homogeneous in their social preference (common types include Nash/selfish, conditional cooperators, and pure altruists). Thus several factors become important in predicting and explaining public goods provision: social preference type, group composition and the information available about the group composition. We use an experimental design and elicit both unconditional and conditional (based on others' contribution decisions) provision strategies from each participant. We categorize subjects into social preference types and recruit selfish and conditional cooperator types for a follow-up experiment. We systematically vary the homogeneity of group composition and the information made available to subjects about group it. We examine the effects of own type, group composition and information on contributions. . We find that both group composition and information impact efficiency.

Keywords: Public Goods, Group Composition, Cooperation

JEL Classifications: H41, C91

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Introduction

Social dilemmas—instances where the individual and social optimum are in direct conflict—pose some of the most interesting and rich problems in social science. Several regularities have emerged out of this research. First, there is significantly more cooperation than predicted if all individuals are purely self-interested, money-maximizing agents. This regularity appears in the field, where individuals voluntarily contribute to charitable organizations or to provide public goods (see e.g. Rose-Ackerman 1996), as well as in context-free laboratory environments, where in one-shot games levels of cooperation are approximately mid-way between the individual and social optimum (Ledyard 1995).

A leading explanation of this phenomenon involves *social preferences* (see e.g. Charness and Rabin 2002; Fehr and Fischbacher 2002; Henrich *et al*. 2001; Roth *et al*. 1991), where individual utility functions might include concerns about altruism (Becker 1974; Andreoni and Miller 2002), warm-glow (Andreoni 1990), inequity or inequality aversion (Bolton 1991; Fehr and Schmidt 1999; Bolton and Ockenfels 2000), or conditional cooperation or reciprocity (see e.g. Frey and Meier 2004; Fehr and Gächter 2000). Previous research has examined the extent to which any one of these factors affects the level of cooperation. This research often fails to control for individual heterogeneity with respect to social preferences.

People are different from each other in many respects. Experimental research has shown that people are not homogenous in their preference for voluntarily providing public goods (see e.g. Fischbacher, Gächter and Fehr 2001). Recognizing that there are distinct social preference types, new factors may become important in explaining and predicting public goods provision: social preference type, group composition and the information available to group members about the group composition. This heterogeneity (and its impact) is reflected in the saying "one bad apple spoils the bunch," or that it only takes one selfish person in a group to ruin the environment for everyone else. While the field informally recognizes that heterogeneous types exist and that group composition matters, this is the first paper to systematically vary and demonstrate its impact.

We analyze the roles that social preference type, group composition and information about group composition have on the ability to attain the efficiency gains associated with the social optimal, both as main effects and when interacting with each other. We report on the results of an incentivized, experimental study of public goods provision. We construct laboratory groups that range in composition from homogeneous groups of the selfish types to homogeneous groups of conditional cooperator types, with the all of the possible heterogeneous groupings in between. In half of the groups, participants are aware of the group composition. We use a particular social dilemma, often studied in public goods provision, a repeated, 3-person VCM.

This design allows the examination of the impacts that social preference heterogeneity and information about group composition have on the voluntary provision of public goods. By controlling group composition and varying the information provided, we are able to overcome confounds that have existed in previous studies, which used random assignment to groups and no information about heterogeneity.

The evidence indicates that there are separate effects of group composition and information on the ability of groups to attain the socially optimal outcome. Individual contributions are higher when the subject is a conditional cooperator and contributions are positively impacted by the information treatment. However, most of this impact comes through people being more responsive to their beliefs, possibly because they are more confident in their estimates. Additionally, we did not find the expected result of full-contributions in the groups with all conditional cooperators. Instead, all participants react more strongly to negative deviations from their expectations (disappointments) than positive ones (surprises), and thus contributions decline even in all-conditional cooperator groups.

In the following section, we describe the literature that lays the groundwork for this study, including work on social preference types, information and group composition. This is followed by a description of the design and implementation. Following sections present the descriptive and econometric results, including: the ability of groups to attain the socially optimal level, the level of individual contributions and the impact of deviations from expectations. we then present some closing comments.

Previous Research

Research into individual and group behavior has shown that individuals are much more cooperative than models of self-interested actors, from both economics and evolutionary biology, predict (see e.g. Axelrod 1984; Boyd and Richerson 2004; Ledyard 1995; Richerson and Boyd 2006). Scholars have attributed this behavior to social preferences (Camerer and Fehr 2004).[1] However, not all individuals have the same social preferences (see e.g. Ahn, Ostrom and Walker 2003).

Heterogeneous Social Preference Types and the Role of Beliefs

The three most common types of players in this game are Nash/selfish, conditional cooperators, and unconditional cooperators. The exact proportions of these types seem to depend on the population under observation and the elicitation mechanism. Our type elicitation

[1] People value not only their own payoffs, but also the payoffs and the intentions of others.

mechanism is based on that of Fischbacher, Gächter and Fehr (2001) who find that the Nash/selfish types make up about 1/3 of their population.[2] In the VCM, this type would contribute zero, no matter what they expect others to contribute, so long as the game horizon is finite. Unconditional cooperators make up about 10% of this same population. These players choose to contribute a high amount to the public good, no matter what others choose to do. Note that for both the selfish and unconditional cooperator types, the slope of own-contributions regressed on expectations of others' contributions is zero, but these two types have very different intercepts: the selfish types have an intercept of zero whereas the unconditional cooperators have an intercept at or near the social optimum.

The largest portion of types in their population, however were the conditional cooperators. Why does this matter? Fischbacher, Gächter and Fehr (2001) and Fischbacher and Gächter (2006) estimate this proportion at around 50% of the population. Individuals who hold this social preference decide whether or not to cooperate based on their beliefs about the potential contributions of others: They give more to public goods (cooperating more) when they believe that others are going to give as well, but do not give (refusing to cooperate) when they believe that others will not. For individuals with this preference, changes in beliefs can have dramatic impacts on behavior.

Other work has demonstrated that individuals often try to match the contributions of the others in their group – in other words, their own contribution is positively related to their expectation of others, based on outside knowledge and past actions of the group members (see e.g. Croson 2007; Croson, Fatas and Neugebauer 2005). While this behavior may be caused by conditional cooperation, it is also consistent with inequality aversion (Bolton 1991; Bolton and

[2] For Kurzban and Houser's (2005) typing mechanism and population, the respective percentages are 20% free-riders, 13% unconditional cooperators and 63% conditional cooperators. For Burlando and Guala (2005), these percentages are 32%, 18% and 35% respectively.

Ockenfels 2000; Fehr and Schmidt 1999; and Ashley, Ball and Eckel 2008; although see Buckley and Croson 2006 for a counterargument). Research into social dilemmas (particularly the Prisoner's Dilemma) has shown that cooperative individuals also expect others to be more cooperative (see e.g. Orbell and Dawes 1993), although the direction of causality is not clear. We focus on the two largest groups: Nash/selfish players and conditional cooperators.[3] Individuals with these types of social preferences are recruited to the lab for the experiment.

Social Preference Types and Group Composition

Two important extensions to traditional economic theory are the recognition that people are heterogeneous in their social preferences and the appreciation that beliefs about the cooperation of others are critical for the expression of some of these social preferences (like conditional cooperation).

Since people are different, how they are grouped together is likely to influence their contributions. For example, grouping individuals by their scores on the Machiavellian scale has been found to affect reciprocity in the trust game (Gunnthorsdottir *et al.* 2002). Previous work finds that the number of free riders in a group causes lower levels of cooperation (Kurzban and Houser 2001, 2005), but their types are classified with the same data that they are trying to explain. Further, they do not systematically control either the group composition or information about it.

Different methods of group assignment in VCMs have been explored as techniques to alleviate free-riding, but these generally focus on an individual's giving history rather than on their social preference type, and sometimes employ a strategic structure that encourages free

[3] Including the unconditional cooperators and other types of preferences would be interesting. However, a full exploration would make the design unwieldy, so we have chosen to focus on the two largest fractions of the population.

riders to hide their type. For example, Gunnthorsdottir, Houser and McCabe (2007), group individuals by their level of contribution (rather than type), but participants do not know about this grouping procedure. Other papers, such as Gunnthorsdottir, Vragov and McCabe (2007) and Gächter and Thöni (2005) rank individuals by their contribution level and use this ranking to determine the allocation to groups. In the former study, the grouping process is common knowledge (creating strategic concerns), whereas in the latter, participants are not informed about the classifications until they have already made their decisions.

These studies reveal several issues addressed with this experimental design. First, in many previous studies, participants are being assigned to groups on the basis of their actions within the game. Free riders may have a strategic reason to hide their type (to be placed in a group with more cooperators). Alternatively, some conditional cooperators may not be revealed to the econometrician because they are in a group of low-contributors: Since conditional cooperators tend to match the contributions of others' in their group, if the group contributions are low then their contributions will be low as well, making their behavior observationally equivalent to that of a free-rider.

Second, these studies do not systematically control the group composition or the information available to the groups. Typically the experiments begin with individuals being randomly assigned to groups, and reassignment occurs only on the basis of previous actions. Gächter and Thöni (2005) vary both group assignment and information concurrently (rather than independently). By holding group composition constant, and just varying the information made available about the group composition, we disentangle these effects.

Only two previous papers elicit social preference types separately from decisions in the context of the game. Burlando and Guala (2005) classify individuals by their social preference type in a two-stage experiment. The first stage has subjects complete a series of experimental tasks and surveys, including a typing task and a repeated VCM. The second stage (a week later) has subjects grouped into completely homogeneous groups by type, but individuals do not know about the composition of the group. They find that, once in homogeneous groups, contributions of conditional cooperators are above that of free-riders and below that of unconditional cooperators. However, they do not adequately address the issue of heterogeneous groups (their heterogeneous groups are their 'remaining players'), and it is unclear what the subjects know about the group composition.[4]

Similarly, Fischbacher and Gächter (2006) use social preference types to classify individuals and look at the consistency of behavior between the initial classification and behavior in the game. They randomly assign individuals to groups, making it difficult to discern the impact that adding one selfish (or cooperative) individual has in destroying (or encouraging) cooperation. They find that the proportion of types in their population is stable: it does not depend on whether the typing task is done before the repeated-play experiment or after it. Additionally, they find that the typing task is consistent with behavior in the repeated play experiment: that is, point predictions can be made for each individual based on their contribution table. Combining these responses with beliefs in the repeated play experiment leads to a round-by-round point prediction that is surprisingly accurate: except for the free-riders, who contribute more than they state in their contribution table. Note that neither paper explores the role that information about the groupings has on cooperation.

[4] As stated by the authors: "It was made clear that the composition of the groups differed from that of the first session" (p. 44). However, there is no mention of whether this meant subjects knew the group composition was homogeneous, or just that these were different groups than those in the first session.

Information

One of the regularities in the literature is that contributions tend to start out relatively high and decline toward zero (but still positive) as individuals repeatedly interact with each other (see e.g. Ashley, Ball and Eckel 2008; and the review in Ledyard 1995). Others have suggested that the rate of decline is associated with the selfish behavior of others, which discourages the conditional cooperators (see e.g. Gunnthorsdottir, Houser and McCabe 2007), but contributions increase again when individuals are re-grouped (Andreoni 1988; Croson 1996). This is inconsistent with subjects simply learning about the game because individuals would start the new game at the endpoint of the previous game if that were the case. It is not, however, inconsistent with the idea of individuals learning about their group members. When re-grouped, individuals may revert to their prior beliefs about the distribution of types in the population and then contributions increase if their group's composition beats their priors and declines if the composition disappoints.

However, most studies that have looked at the role of information in determining provision have focused on information about contributions rather than information about group composition or social preference types (see e.g. Brandts and Schram 2001; Page *et al.* 2005). To the best of the author's knowledge, no one has specifically focused on the impact of revealing information about social preference types.

In sum, the two largest proportions of social preference types in the population are selfish or free-riders and conditional cooperators or reciprocators. For this second group, information about group members is particularly important since their contribution decision is based largely on beliefs. Though others have started to research the impacts of group composition and information on efficiency in a public goods environment several shortcomings persist. We contribute to this literature by systematically varying both the group composition and information about the group composition to tease apart the impacts of each of these factors on the ability of groups to attain the socially efficient outcome.

Experimental Design and Implementation

Data include two waves of experimental sessions. In the first wave, individuals complete a survey and participate in an internet experiment which allows the identification their social-preference type. We rely on the methodology of Fischbacher, Gächter and Fehr (2001; see also Fischbacher and Gächter 2006) to elicit the types of the participants. Since this design is based on theirs, we will take a moment to describe it before continuing.

First, in a one-shot game, participants decide on an ‘unconditional’ contribution to a public good. Next, the strategy method is used to elicit the donation decision of each individual for each possible (average) contribution by the other group members. To make the elicitation procedure incentive compatible, a one-shot game is then played with four players, chosen at random. Three of these players (again, randomly chosen) contribute based on their reported unconditional strategies while the final player contributes based on his reported conditional strategy (conditional on the contributions of the other three). Responses from the conditional strategies are used to determine the individual’s type. Conditional strategy of a Nash type involves always contributing zero, whereas a strategy profile of a conditional cooperator involves higher contributions as expectations of others’ contributions increase.

Finally, participants played a ten-round VCM where beliefs about the other group members’ contributions were elicited and groups were randomly re-assigned each period in a “strangers” protocol (Croson and Andreoni 2008). The order of the tasks was blocked. These authors then use the data from the conditional strategies (types) to predict (statistically) behavior in the (randomly assigned) groups and find a high degree of consistency between the types and the observed decisions in the VCM.

Our experimental design differs in a few dimensions that should not substantially affect the classifications.[5] We conduct the type elicitation task on a different day than the repeated-play experiment. Conducting the type elicitation task in advance allowed selective recruitment of individuals to the lab and appropriate control of the groupings in the subsequent VCM. Group size is three and there is a higher marginal per capita return (MPCR) to match the VCM game in the second stage, as described below.

In the typing study, individuals who always choose to donate zero (or a nominal amount) to the group account are classified selfish while individuals whose contributions increase with the contributions of others are categorized as conditional cooperators. We then use this information to expressly recruit individuals who are of these types into the lab for the VCM study. Since we know the individuals' types, we can vary the homogeneity of the group composition in both a perfect and incomplete information treatments.

In the second wave, individuals are placed into homogenous or heterogeneous groups (based on their social preference types) and participate in a repeated linear VCM. The information made available to participants about the distribution of the social preferences of other group members varies across the information treatments: KNOWN DISTRIBUTION and UNKNOWN DISTRIBUTION. Compared with Fischbacher and Gächter (2006), in this part of the experiment we use stable (rather than re-matched) groups, in order to identify the impact of group composition and information about it, which is not possible when the group composition

[5] Screen shots containing the instructions for the typing task as well as the present study are available at : http://cbees.utdallas.edu/projects_pg.php

changes each period. We use a group size of three rather than four to simplify our design and reduce the number of subjects necessary. Finally, we use a higher MPCR to provide greater tension between the Nash Equilibrium and Social Optimal. While the partners design, the smaller group size and the higher MPCR might increase the *level* of contributions observed compared to Fischbacher and Gächter (2006), these parameters were constant across all groupings and treatments and should not impact comparisons between treatments.

Table 1 describes the subject sample. Subjects were recruited by type (selfish or conditional cooperator) and randomly assigned to group composition and information treatment.[6]

[Table 1]

In the lab, participants are grouped into either homogeneous or heterogeneous groups of three, including: homogeneous groups of all selfish players (S, S, S), homogeneous groups of all conditional cooperators (CC, CC, CC) and heterogeneous groups with two of one type and one of another (S, S, CC) and (CC, CC, S). Participants first play a one-shot VCM with no feedback (Round 0). Subjects are then re-grouped into a different group. These groups are fixed for 15 rounds (Rounds 1-15). Individuals make contribution decisions each round, and after each round they receive information about their payoff. In addition, after the contribution decisions have been made but before the results are revealed, beliefs are elicited, with payment for accuracy based on a quadratic scoring rule.[7]

[6] There are no significant differences in demographics between the Known and Unknown distribution treatments at $p<0.05$, except the following: Asian ($p=0.01$). There are several differences at $p\leq 0.10$, including: GPA ($p=0.05$), White ($p=0.06$), Other ($p=0.07$), Senior ($p=0.10$), Number Recognize ($p=0.10$), Number Friends ($p=0.07$). Due to difficulty recruiting the required number of the various types of subjects, a limited number of experienced subjects were recruited. This analysis has been conducted with and without controls for these subjects, and any differences have been reported.

[7] Individuals received an additional 5 points for a correct prediction of the average allocation of the other two group members and 0 points if the guess was maximally far away.

For each grouping, we vary the information available about the distribution of types in the group: In half of the treatments the distribution is known to the players, and in the other half the distribution is not known. In the KNOWN DISTRIBUTION treatment, participants are told the distribution of social preference types in their group. For example, suppose a selfish type (called type A) is in a group with two conditional cooperator-types (called type B), then he will receive the following message:

[Figure 1]

In the UNKNOWN DISTRIBUTION treatment, the message is the following:

[Figure 2]

In both treatments, participants see information about their own type. Thus, the only informational difference between these two treatments is the *initial* message that subjects receive about their group members. All of the other factors between the two treatments are the same. This design involves controlled group composition, with types identified before the beginning of the game (rather than endogenously through their play). It thus it allows us to identify the effects of group composition on contributions. It also allows us to separate the effects of group composition and information about the composition. Most importantly, it allows us to examine the differential impact that information has on different group compositions. This interaction effect may help explain why similar policies for overcoming public goods under-provision succeed in some groups and fail in others.

In all treatments decisions are single-blind. There are 15 contribution periods, which is announced in advance. Between periods, participants see their own payoff from the last round, as well as their payoff from the belief elicitation. With this feedback across both treatments, we can focus solely on the impact of knowing (or not) the distribution of types in the group.

The endowment is 20 tokens, and the MPCR is 0.5. Since computations can be confusing and overwhelming for participants, the interface includes a design-specific calculator which allows participants to "practice" by entering contributions themselves and each of the other players. The calculator then displays each individual's payoffs, contingent on the information entered.

Once the experiment had ended, participants complete a demographic and social preference survey. In this study, we had 102 participants in 10 sessions.[8] Participants were paid based on a conversion rate of four experimental points to $1. The subjects earned $17.58 on average ($11.72 min and $23.94 max) for the 45 minute session in addition to any show-up fee that they received.

Descriptive Results

Table 2 shows the average individual contribution to the group account, by treatment and group composition. All *n*'s are for the number of subjects in that grouping and information treatment. The 'before' results show the contributions for Round 0: the contributions that are made before individuals receive the information screen described above. Remember that this round has the same types and group composition, but this is a one-shot interaction and subjects have not yet been told any information about either their own type or the types of their counterparts. The 'after' columns show the average group account contribution for the first round after the treatment change (Round 1). Subjects are re-grouped between R0 and R1 and receive no feedback from R0 until the end of the session. Recall that, on the information screen preceding the R1 decision, subjects are informed about their own type in both information conditions, but only informed about the types of their counterparts in the KNOWN DISTRIBUTION treatment.

[8] This includes 83 inexperienced and 19 experienced subjects.

[Table 2]

Comparing the contributions before and after the information treatment for each of the groupings allows us to confirm that later results are not driven by the fact that subjects are told their own type, which is information that the subjects presumably already possess. A series of before-after pair wise tests confirm that there are no significant differences between the average contribution for either the KNOWN or UNKNOWN DISTRIBUTION treatment (all p-values greater than p=0.35).[9]

Holding group composition constant allows examination of the impact of information about group composition on individual contributions to the group account. Using a t-test of means comparing Round 1 contributions by treatment, there are no statistically significant impacts of information on cooperation for groups composed of zero (p=0.69), one (p=0.78) or two (p=0.77) conditional cooperators, even though more is contributed in the KNOWN DISTRIBUTION treatment in all three cases. There is significantly more cooperation in the KNOWN DISTRIBUTION treatment for the group composed of three conditional cooperators (p=0.03). This result indicates that conditional cooperators need to know that there are "no bad apples" (no selfish types) in their group for their cooperative tendencies to be expressed.

Next, look at the difference in individual contributions as more conditional cooperators are added to the group. In Round 1 of the KNOWN DISTRIBUTION treatment, contributions increase each time an additional conditional cooperator is added and there is a large and statistically significant difference between the group with three selfish players and the group with three conditional players (10.11 tokens, p=0.004). Contributions in the group with three conditional players in the KNOWN DISTRIBUTION treatment are also larger than contributions in the groups with two (p=0.02) or one (p=0.003) conditional players. This is not the case for the

[9] All p-values are for a two-tailed t-test of means, unless otherwise stated.

UNKNOWN DISTRIBUTION treatment. Though the same general trend of increasing contributions with increased cooperators holds, none of the differences are statistically significant (all p>0.12). This seems to indicate that both information and group composition separately impact the willingness of individuals to contribute to the group account, but that there is an interaction effect.

To investigate this more closely, it is important to understand the role that an individual's own social preference type plays in the decision to contribute. Figure 3 shows the average individual contributions for both the selfish and conditional cooperator types in both treatment conditions. Contributions are slightly higher for both selfish and conditional cooperator types in the KNOWN DISTRIBUTION treatment than they are in the UNKNOWN DISTRIBUTION treatment. These differences are not statistically significant, however, in round-by-round means tests, though they are significant in OLS regressions (not shown). Consistent with Fischbacher and Gächter (2006) and Kurzban and Houser (2005), conditional cooperators contribute more in both information treatments than do selfish types, and these differences are statistically significant. This provides some preliminary evidence that the impact on group contributions of the number of conditional cooperators in the group is caused by group composition, rather than some sort of priming effect.

[Figure 3]

Figure 4 compares the average amount that individuals contribute to the group account in both the KNOWN and UNKNOWN DISTRIBUTION treatments for each of the four group compositions. There is a surprising level of contributions in the S, S, S grouping, given that the selfish players were specifically recruited because they had revealed in the type elicitation task that they would not contribute. Contributions increase with the number of conditional cooperators, and the information treatment has a larger impact with more conditional cooperators.

[Figure 4]

Separate OLS regressions (not shown) for each grouping confirm that the impact of information increases the level of contributions in both S, S, S and CC, CC, CC groupings, but that there are no significant differences for the other groupings.

Analysis: Group Contributions

The central question is the following: what are the impacts of group composition and information on the ability of groups to attain the socially efficient outcome? We first approach the issue of efficiency by exploring the factors that impact the level of group contributions. For ease of interpretation, the dependent variable is the percentage of possible contributions to the group account. This variable has the nice property that the value is 100 if contributions are at the socially optimal level and at zero if contributions are at the Nash Equilibrium.

Since we have a panel data set with both time variant and time invariant variables and contributions censored at 0, we model the percent efficiency using a random effects Tobit in table 3. The dependent variable is group *g*'s contribution as a percentage of the maximum contributions possible at round *t*. Independent variables include: the round, which allows for a time trend, beliefs about the average contribution of others in the group in round *t*, the number of conditional cooperators in group *g*, and the information available to the group.

[Table 3]

The first column presents the main effects. Consistent with previous research, contributions decline over time and beliefs are positively related to allocations. Contributions are higher in the KNOWN than the UNKNOWN DISTRIBUTION treatment. Groups with more conditional cooperators have higher contributions.[10]

The second column allows for interaction effects between the information treatment and other explanatory variables. The information treatment is working through the interactions. Specifically, groups in the KNOWN DISTRIBUTION treatment are more responsive to their beliefs, possibly because individuals are more confident in their estimates of others' giving (although unfortunately confidence was not elicited). Group composition (number of conditional cooperators in the group) is significantly and substantially related to the level of efficiency, but this effect does not interact with the information. Another way to look at the impact of the treatment and group composition on the ability of groups to attain socially efficient outcomes is to explore how the factors impacting how decisions change over the rounds: table 4 presents the results. Rounds are grouped: 1-5, 6-10 and 11-15.

Knowing the distribution of types results in a large initial (R1-R5) increase in contributions, working through the interaction effects. In the middle periods, choices are driven completely by beliefs, with other factors significant again toward the end rounds. Contributions are still more responsive to beliefs (even in the last rounds) in the KNOWN DISTRIBUTION treatment, and there is a negative interaction effect between the number of conditional cooperators in the group and the information treatment.[11]

[Table 4]

[10] There is no difference in the results when using dummy variables for the number of conditional cooperators in the group (Main effect LnL=-1662.38; Interactions LnL=-1651.58) and using a variable that pools this information (Main effect LnL=-1662.57; Interactions LnL=-1652.49), so I present the simpler model.

[11] Note that the sign on the coefficient was negative in the full model of table 1.3 but it was not statistically significant.

While the first interaction effect (beliefs and information) was anticipated, the second (group composition and information) was not. However, this may explain why group contributions are lower in this study than in previous group composition studies where "high givers" were put together (Gächter and Thöni 2005). In order to better understand these patterns, we turn to the analysis of individual contributions.

Analysis: Individual Contributions

Our data involves panel data set with both time variant and time invariant variables and contributions censored at 0 and 20. Therefore, contributions are analyzed using a random effects Tobit of the individual decision to contribute to the group account, based on individual social preferences, information treatment and group composition. The dependent variable is individual i's contribution decision at round t, C_{it}. This contribution decision is a function of the round, R_t, which allows for a time trend. In addition, we hypothesize that the provision decision depends on beliefs about the average contribution in round t, B_{it}, the number of conditional cooperators in individual i's group, N_i, an individual's own type, T_i and the information available to individual i about her other group members, I_i.

Table 5 presents these results separately for the selfish and conditional types as well as for the pooled case. In the combined model, conditional cooperators are contributing significantly more to the group account than the selfish types are and contributions decay over time for both types of players.

Individuals classified as conditional cooperators choose their actions based on their beliefs about the contributions of others. They give more to public goods (cooperating more) when they believe that others are going to give as well, but do not give (refusing to cooperate) when they believe that others are not going to cooperate. In contrast, selfish types were defined as those who give zero, regardless of the contributions of others. We thus hypothesized that beliefs would be positively and significantly related to the behavior of conditional cooperators, but not to the behavior of the selfish types. However, this turned out not to be the case. Both the selfish and conditional types respond equally and positively to their beliefs. Selfish players have lower beliefs than the conditional players do (5.20 versus 9.06 pooled over all individuals and rounds, t-test p=0.00). However, even controlling for beliefs, conditional players contribute significantly more to the group account than the selfish players do.

[Table 5]

Selfish players decrease their contributions when there are more conditional players in the group, but conditional players are non-responsive to the number of conditional cooperators in their group (controlling for beliefs), which is the opposite of what was hypothesized. It appears that conditional players are paying attention to people's actions (via beliefs), but not their types.

Additionally, conditional players are (marginally) reacting to the information treatment, whereas the selfish players are unresponsive to this treatment. However, group composition and information about the group composition may impact the contribution decision not only as main effects but also by interacting with other factors that impact the decision.

Table 6 presents results from a random effects Tobit where the information treatment is allowed to interact with the round, beliefs, the group composition and the social preference type. The first column presents the results for the selfish players, the second column shows the conditional players, and the final column pools the data from the two types. Controlling for the interaction effects, there is a much stronger relationship for the main effect of the number of conditional cooperators in the group and the information treatment on the contribution decision of the conditional cooperators. Although the information treatment was only marginally significant on its own (table 5), the influence of information is highly significant when interacted with the other variables.

For conditional cooperators, the information treatment (marginally) impacts the decay rate. There is a steeper decline for the conditional players in the KNOWN DISTRIBUTION treatment than those in the UNKNOWN DISTRIBUTION treatment, which was observed graphically in figure 3.

[Table 6]

Both conditional and selfish players remain responsive to their beliefs about others' contribution. But types are *more* responsive to their beliefs in the KNOWN DISTRIBUTION treatment.

Conditional cooperators' contributions increase with the number of conditional cooperators in the group, but this effect is reduced in the KNOWN DISTRIBUTION treatment. In contrast, selfish players' decisions are not responsive to the group composition (as predicted) or its interaction with information.

Deviation from Expectations

An additional question raised by the results in the previous sections is why the contributions of the conditional cooperators decline over time, even in the groups composed of all conditional cooperators. To address this we examine the factors that impact the changes in contributions from one period to the next ($C_t - C_{(t-1)}$), presented in table 7.

[Table 7]

Specifically, we are interested in how individuals respond to their expectations being incorrect; when group members either contribute more or less than what they expected of them in the previous period. When expectations are disconfirmed, this might lead contributors (especially conditional cooperators) to update their beliefs and thus their own giving. One reason for the decline in contributions might be that this updating is more extreme (or stronger) when individuals are disappointed by the contributions of others, than when they are pleasantly surprised. We construct two variables to address this issue: *Lag Above Belief* and *Lag Below Belief*. Lag Above Belief is defined as the lagged average contribution of the other two group members minus the lagged belief about those contributions if this difference is greater than zero, and zero otherwise. Lag Below Belief is the absolute value of this same difference if the difference is less than zero, and zero otherwise. Both of these variables can be interpreted with positive coefficients meaning an increase in contributions and negative coefficients meaning a decrease in contributions.

Individuals do indeed respond differently to group contributions that are above or below their beliefs. If the group contributions are greater than their beliefs, they increase their contributions, but only marginally. If the group contributions are less than their beliefs, they decrease their contributions significantly.

The analysis includes controls for the lagged change in contributions, to allow for path-dependence in the decisions. The previous change in contributions is significantly related to the current change, but people tend to move in the opposite direction; if they previously increased their contribution they are more likely to decrease it this round. Type, group composition, and the number of conditional cooperators in the group do not impact the changes in contributions (and there are no interaction effects between the treatment and these factors, regression not shown).

Since there is no difference in updating behavior based on group composition, information treatment, or type, the decline in contributions even among conditional cooperators appears to be based on the stronger reaction of individuals to negative deviations from their expectations.

Discussion

Does one “bad apple” really spoil the bunch? The number of conditional cooperators in a group positively and significantly impacts group contribution. As in Kurzban and Houser (2001, 2005) there are lower levels of group contributions in groups with more free riders. While “bad apples” are surely bad, the impact is gradual rather than all-or-nothing. Selfish players take advantage of others when given the opportunity. But, so long as they are not in the majority, the impact of the “good apples” far outweighs that of the “bad apples.”

As expected, individual contributions are higher when the subject is a conditional cooperator and contributions are positively impacted by the information treatment. Additionally, information about group composition has interesting and important interaction effects. First, information makes subjects more responsive to their beliefs, which in turn positively impacts contributions. Second, information negatively interacts with the number of conditional players in the group. In other words, given the knowledge and opportunity, individuals take advantage of the conditional cooperators.

Taken together, this evidence indicates that there are separate effects of group composition and information on the ability of groups to attain the social optimal outcome. Conditional players tend to hold higher beliefs about others’ contributions than selfish players, and information makes subjects and groups more responsive to their beliefs, possibly because they are more confident in their estimates.

Additionally, we did not find the expected result of full-contributions in the groups with all conditional cooperators. Instead, all participants react more strongly to negative deviations from their expectations (disappointments) than positive ones (surprises), and thus contributions decline even in all-conditional cooperator groups. This does not support the Gunnthorsdottir, Houser and McCabe (2007) claim that it is the selfish types that are discouraging the conditional cooperators. Rather, the conditional cooperators are disappointing each other. A word of caution is warranted here. The impact of information was greatest in the initial periods. In the linear VCM there is only one Nash Equilibrium, and the pull of that equilibrium remains throughout the game.

This research increases our knowledge of the mechanisms that underlie cooperative behavior, advancing our understanding of how agents react to changes in the types of individuals with whom they interact. We believe that the next step is to integrate these behavioral principles into new theoretical models of cooperation—models that recognize the roles that heterogeneity in the social preference domain and beliefs about group composition have on behavior.

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Table 1. Description of sample

Variable	Unknown *n=54*	Known *n=48*
Demographics, % of sample		
Female	35.2	35.4
Employed	55.6	43.8
Religious services, 1+ per week	27.8	31.3
Greek	13.0	14.6
Average Age, years	22.1	22.0
GPA, points	3.4	3.6
Ethnicity, % of sample		
White	59.2	77.1
Black / African American	3.7	2.1
Hispanic	7.4	2.1
Asian	27.8	8.3
Other	1.9	10.4
Cohort, % of sample		
Freshmen	5.6	4.2
Sophomore	18.5	25.0
Junior	31.5	43.8
Senior	42.6	27.1
Major, % of sample		
Economics	5.6	12.5
Other Social Sciences	12.9	14.6
Business	16.7	16.7
Engineering	22.2	12.5
Mathematics	1.9	6.3
Computer Science	11.1	10.4
Science	27.8	22.9
Humanities	5.6	4.2
Number of subjects that an individual…		
Recognizes	1.3	0.9
Considers friends	0.8	0.3

Table 2. Average individual contribution before and after information, by grouping and treatment (std. dev.)

	Information			
	Known Distribution		Unknown Distribution	
Groupings	Before (R0)	After (R1)	Before (R0)	After (R1)
S, S, S	6.67 N=9 (8.66)	5.89 N=9 (7.47)	5.44 N=9 (8.62)	4.44 N=9 (7.68)
S, S, CC	3.93 N=15 (6.53)	6.67 N=15 (7.19)	5.72 N=18 (6.90)	5.94 N=18 (7.64)
S, CC, CC	10.13 N=15 (6.99)	9.06 N=15 (7.40)	7.08 N=12 (7.27)	8.25 N=12 (7.06)
CC, CC, CC	13.78 N=9 (5.83)	16.00 N=9 (5.17)	9.53 N=15 (7.41)	9.53 N=15 (7.41)

Table 3: Percent of possible group contributions, random effects Tobit

Variable	Main Effect	Interactions
Round	-0.960***	-0.809***
	(-7.94)	(-4.89)
Believed % Contributed	0.765***	0.610***
	(15.70)	(9.02)
Known Distribution	4.228**	-0.788
	(2.13)	(-0.18)
Number CC	5.802***	6.615***
	(5.19)	(4.67)
Round*Known	…	-0.268
		(-1.12)
Belief*Known	…	0.401***
		(4.05)
Number CC*Known	…	-3.614
		(-1.47)
Constant	-1.670	-0.605
	(-0.66)	(-0.18)
P	0.486	0.447
LnL	-1662.57	-1652.49
Wald χ^2	602.53	654.55

*p<.10 **p<.05 ***p<.01

Note: t-stats in parentheses. 91 left-censored observations, 419 uncensored observations

Table 4: Percent of Possible Group Contributions, by Rounds
Random Effects Tobit

Variable	R 1- R 5		R 6 – R 10		R 11 – R 15	
	Main Effect	Interaction	Main Effect	Interaction	Main Effect	Interaction
Round	-1.325**	-0.868	-0.167	0.227	-0.360	-0.600
	(-2.09)	(-0.99)	(-0.30)	(0.29)	(-0.64)	(-0.77)
Belief % Contributed	0.666***	0.518***	1.098***	0.964***	1.052***	0.832***
	(6.66)	(4.53)	(10.52)	(7.78)	(12.56)	(8.78)
Known Distribution	12.009***	7.192	2.806	3.184	6.693**	-3.870
	(3.33)	(0.87)	(0.79)	(0.28)	(2.14)	(-0.25)
Number CC	7.453***	9.744***	-5.05	0.802	1.453	3.757**
	(3.63)	(4.13)	(-0.21)	(0.30)	(0.76)	(2.21)
Round*Known	…	-1.063	…	-0.783	…	0.450
		(-0.86)		(-0.70)		(0.40)
Belief*Known	…	0.591***	…	0.325*	…	0.583***
		(3.42)		(1.70)		(4.16)
Number CC*Known	…	-10.339***	…	-4.187	…	-10.211***
		(-2.63)		(-0.97)		(-3.37)
Constant	-4.622	-3.710	-10.475*	-10.611	-15.560*	-7.823
	(-0.93)	(-0.60)	(-1.73)	(-1.36)	(-1.89)	(-0.72)
P	0.430	0.373	0.468	0.420	0.410	0.210
LnL	-606.48	-599.64	-559.00	-557.40	-497.37	-490.71
Wald χ^2	145.18	189.24	202.71	224.17	264.32	429.75

*p<0.10 **p<0.05 ***p<0.01
Note: z-stats in parentheses.

Table 5. Main effects: random effects Tobit for the amount sent to the group account

Variable	Selfish	Conditional	Combined
Round	-0.490***	-0.309***	-0.354***
	(-5.44)	(-7.53)	(-9.08)
Belief	1.144***	1.033***	1.053***
	(10.12)	(14.30)	(17.77)
Number CC	-1.767**	0.644	-1.597***
	(-1.99)	(0.68)	(-2.66)
Known Distribution	1.481	1.855*	1.830**
	(1.02)	(1.69)	(2.33)
Conditional	…	…	8.568***
			(7.23)
Constant	-2.041	-0.088	-3.749***
	(-1.19)	(-0.03)	(-3.11)
P	0.786	0.602	0.649
LnL	-921.05	-1782.96	-2739.12
Wald χ^2	140.25	307.41	568.91
Observations (Ss)	735 (49)	795 (53)	1530 (102)
Censoring – Left	493	149	642
. Right	24	116	140

*p<.10 **p<.05 ***p<.01

Note: t-stats in parentheses.

Table 6. Interactions: random effects Tobit for the amount sent to the group account

Variable	Selfish	Conditional	Combined
Round	-0.397***	-0.235***	-0.287***
	(-3.07)	(-4.26)	(-5.41)
Belief	0.813***	0.921***	0.820***
	(5.40)	(10.32)	(11.51)
Number CC	-0.558	2.039**	1.109
	(-0.37)	(2.50)	(1.36)
Known Distribution	-0.479	5.259**	4.462***
	(-0.18)	(2.01)	(2.68)
Conditional	…	…	5.394***
			(3.11)
Round*Known	-0.103	-0.177**	-0.137*
	(-0.59)	(-2.17)	(-1.79)
Belief*Known	0.639***	0.362***	0.536***
	(3.00)	(2.64)	(4.75)
Number CC*Known	-1.257	-1.900*	-4.001***
	(-0.69)	(-1.65)	(-3.54)
Conditional*Known	…	…	3.663
			(1.63)
Constant	-2.166	-3.628	-5.663***
	(-0.99)	(-1.93)*	(-5.37)
P	0.737	0.621	0.682
LnL	-917.49	-1775.80	-2724.11
Wald χ^2	154.80	476.06	670.14

*p<.10 **p<.05 ***p<.01

Note: t-stats in parentheses.

Table 7. Changes in contributions and deviations from expectations
Prais-Winsten AR(1) regression with individual clusters

Variable	Combined
Lag Δ Contribution	-0.239***
	(-9.86)
Lag Above Belief	0.054*
	(1.79)
Lag Below Belief	-0.067**
	(-2.14)
Number CC	-0.002
	(-0.02)
Known Distribution	-0.102
	(-0.90)
Conditional	0.109
	(0.63)
Constant	0.038
	(0.33)
Observations (clusters)	1530 (102)
R^2	0.13
F (Pr > F)	20.26

*p<.10 **p<.05 ***p<.01
Note: t-stats in parentheses.

Figure 1. Screen shot: known distribution treatment

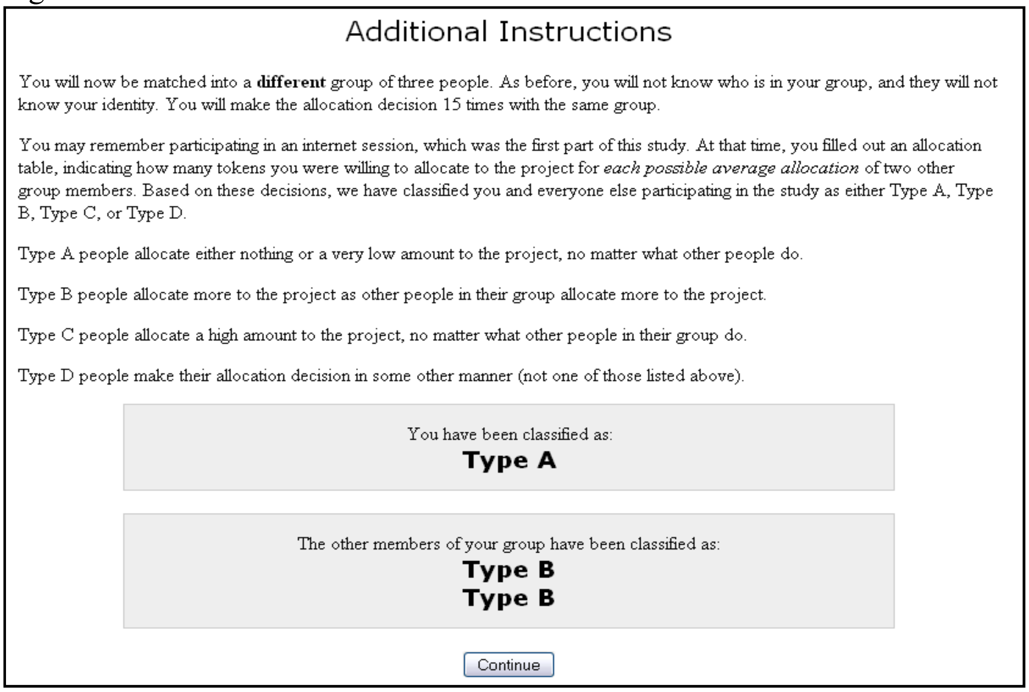
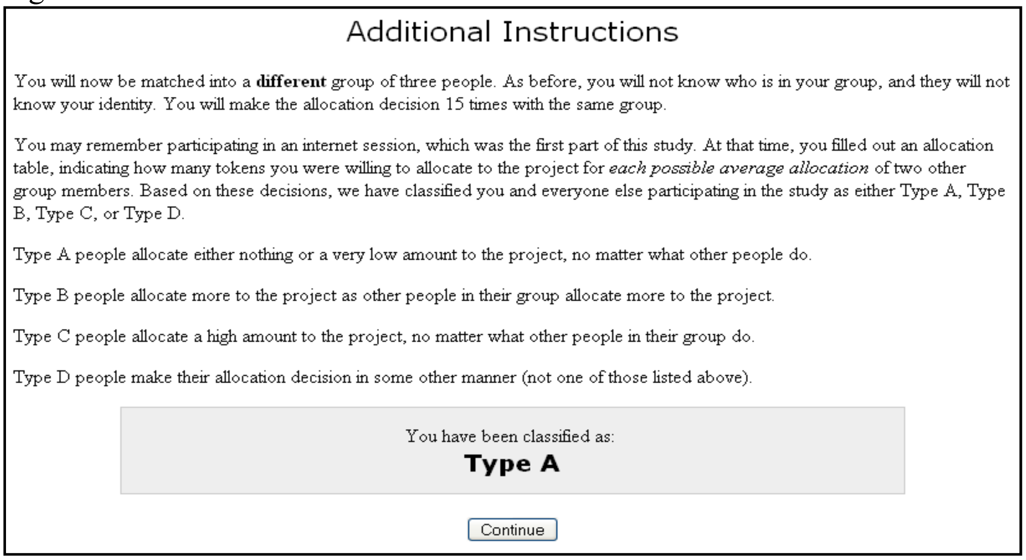


Figure 2. Screen shot: unknown distribution treatment



Additional Instructions

You will now be matched into a **different** group of three people. As before, you will not know who is in your group, and they will not know your identity. You will make the allocation decision 15 times with the same group.

You may remember participating in an internet session, which was the first part of this study. At that time, you filled out an allocation table, indicating how many tokens you were willing to allocate to the project for *each possible average allocation* of two other group members. Based on these decisions, we have classified you and everyone else participating in the study as either Type A, Type B, Type C, or Type D.

Type A people allocate either nothing or a very low amount to the project, no matter what other people do.

Type B people allocate more to the project as other people in their group allocate more to the project.

Type C people allocate a high amount to the project, no matter what other people in their group do.

Type D people make their allocation decision in some other manner (not one of those listed above).

You have been classified as:

Type A

Continue

Figure 3. Average individual contribution per round, by treatment and type

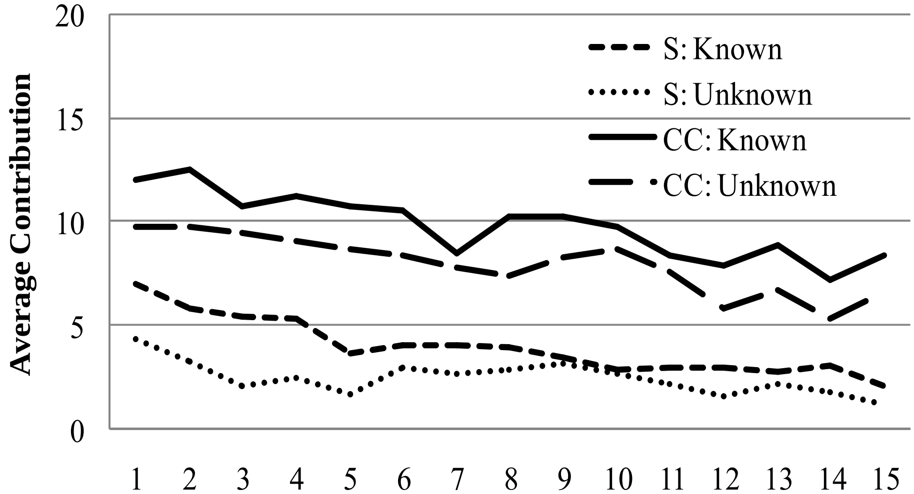


Figure 4. Average individual contributions per round, by group composition and information treatment